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Analysis of Optimal Allocation and Efficiency Enhancement of Farming Cultural Resources under Rural Revitalization Strategy Based on Linear Programming Algorithm

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Abstract Farming culture is an important support for current rural revitalization. The inheritance of farming culture can drive the new development and cultural prosperity of the countryside. In this paper, we establish a model of farming culture resource-task allocation problem, and use the combination of column enumeration method and pairwise test method to solve the linear planning model of farming culture resource allocation. In order to reduce the amount of computation, an improved genetic algorithm incorporating a learning mechanism is designed. The algorithm uses greedy operator to encode the chromosomes, and considers a single chromosome as an orderly arrangement of several villages, and finally determines the overall allocation plan by sequentially allocating farming cultural resources to villages. The improved genetic algorithm incorporating the learning mechanism is used to solve the linear planning model of farming culture resource allocation to find the allocation efficiency of farming culture resources before and after resource allocation in 2024. The combination of each key resource input after the optimization process according to the linear planning model of optimal resource allocation is (17.5263, 23.6659, 23.2143, 24.3662, 23.0045, 23.8596, 24.6365, 24.9631). The resource allocation capacity of farming culture is 85.0027. The enhancement of resource allocation efficiency of farming culture is more conducive to the development of rural revitalization.

Index Terms learning mechanism, genetic algorithm, resource allocation, farming cultural resources

I. Introduction

Farming culture is a kind of cultural form based on agricultural production and life style, and based on agricultural production and life style, it is a kind of crystallization of human wisdom in the state of natural production and life [1]-[3]. Farming culture is the crystallization and embodiment of the traditional culture of the Chinese nation, showing unique cultural characteristics and connotations in the current complex and diverse cultural system, which is based on traditional folklore and folk customs, and in China, it is a wide range of a cultural form [4]-[7]. Farming culture not only determines the course of the history of the Chinese nation and writes the greatness and pride of the Chinese people, but still permeates our lives today, especially in all aspects of social life in the countryside [8], [9]. However, with the development of the countryside, the allocation and efficiency of farming culture resources are facing many challenges, and as the strategy of rural revitalization has achieved remarkable results in China, the optimization of the allocation and efficiency of farming culture resources has ushered in an opportunity [10]-[12].

Rural revitalization strategy is an important initiative in the great cause of socialism with Chinese characteristics, aiming at realizing modern national agriculture, beautiful countryside and farmers' prosperity, and the optimal allocation of resources is one of the core contents of the rural revitalization strategy, which involves rural land, agricultural factors of production, scientific and technological talents, capital inputs and other aspects [13]-[16]. The optimization of resource allocation of rural revitalization strategy firstly requires comprehensive resource investigation and planning [17]. By systematically collecting, organizing and analyzing the natural resources, human resources, social resources and economic resources of the countryside, it provides a scientific basis for the optimal allocation of resources [18]-[20]. The optimization of resource allocation of rural revitalization strategy is an important task to realize rural revitalization, and only through scientific, reasonable and effective resource allocation can we stimulate the vitality of the countryside and promote the smooth implementation of rural revitalization strategy [21]-[23].

This paper establishes an exact linear model for the resource allocation problem in which the types of resources are often ignored. Combining the various cultural resources included in the excellent traditional farming culture, set the target of farming culture resource allocation and the allocated state of farming culture resource allocation. Collect data on various inputs of farming cultural resources in the cooperative sector of rural revitalization, and establish a linear planning model of farming cultural resource allocation. The linear programming model is solved using the column enumeration method with the pairwise test method. Simplify the genetic operation of the genetic algorithm, incorporate the learning mechanism, and design an improved genetic algorithm incorporating the learning mechanism to solve the linear planning model of agricultural and cultural resource allocation.

II. Agrarian culture-related

II. A. Main contents of excellent traditional farming culture

The unique farming culture has been formed in the development of agricultural society for thousands of years, showing explicit and implicit cultural qualities in terms of objects, institutions, behaviors and consciousness [24], [25].

(1) Explicit culture

(a) Physical culture

The culture of human society includes material civilization and spiritual civilization, and material civilization involves the means of production and human clothing, food, housing and transportation. The mode of production and products of agricultural society include all aspects of farming production and life, such as water conservancy facilities, equipment, clothing and food, agricultural dwellings, and living utensils, etc. These material contents constitute the farming material culture.

(b) Institutional Culture

As agricultural production is affected by many factors, the labor habits formed by people in the long period of agricultural production will affect other aspects of production and life. On this basis, adhering to the concept of “agriculture-oriented” construction guidelines, corresponding systems are formulated to regulate the behaviors of members of the rural community and regulate the relationship between them, such as land systems, such as land systems, planting systems, clan systems, village management systems and so on.

(2) Hidden Culture

(a) Behavioral culture

In agrarian society, the village is a common carrier for people's life and production, and in this social space composed of blood and geography, people are more familiar with each other. Therefore, the traditional village is a “society of acquaintances”. Morality is the bond that keeps people's relationship, and moral governance is an important way of village governance. Some behavioral norms, such as respect for the elderly, love for the young, hard work, observance of public morality, mutual help, etc., are also permeated into the farming culture, and the manners and customs and interpersonal habits formed in these behavioral norms form a part of the hidden culture of the farming society.

(b) Consciousness culture

In farming society, people live in clusters according to blood relations, which also gives farming culture a collectivist connotation, and the national sentiment of village members is built on a sense of belonging to and identification with the village community, which then gradually develops and rises to the identification with the nation and the state. Because of the specific geographic environment, the influence of social space and the needs of agricultural production, people in their conscious activities and social practices produce a cultural layer composed of subjective factors, including values, ways of thinking, aesthetic tastes, racial character and religious beliefs, which become another part of the hidden culture of the rural society.

II. B. The significance of the inheritance of farming culture under the strategy of rural revitalization

Agricultural production, which has continued since the Neolithic Age to the present day, is the basis for the formation and development of traditional societies, as well as the source and driving force behind the continuous evolution of farming culture.

Inheriting farming culture is not only conducive to promoting the implementation of rural strategy, driving the new development and cultural prosperity of the countryside, but also helps to enrich people's spiritual world and increase cultural confidence and cultural identity.

(1) Inheritance of farming culture is conducive to the development of agricultural production and food security.

The traditional agricultural country emphasizes that “the country is based on the people, and the people are based on food and clothing”. Therefore, the traditional farming culture is rich in agricultural ideas, that “if farming is not done, there will be a lack of food”, and that agricultural production activities that provide food for human beings are the fundamental basis for people's survival.

The inheritance of farming culture is conducive to the integration of agricultural thinking into the overall construction of the country, so as to make people regain the reverence and respect for the land and agriculture, improve the social status of farmers, thereby stimulating people's enthusiasm for agricultural production and giving full play to the fundamental role of agriculture in the national economy.

(2) The inheritance of farming culture is conducive to the formation of a good civilization and the construction of a harmonious countryside.

The inheritance of farming culture is conducive to making the excellent traditional moral code return to people's lives and restraining people's code of conduct. The excellent connotation of father's kindness and filial piety, brother's friendship and brother's respect, respect for the old and love for the young, valuing righteousness over profit, etc. contained in the traditional farming culture is conducive to providing nourishment for the construction of good rural civilization, and promoting the construction and development of the harmonious socialist countryside in the new era.

(3) Inheriting farming culture is conducive to the protection of agricultural cultural heritage and the development of brand agriculture.

Inheritance of farming culture is conducive to make people pay more attention to and protect agricultural cultural heritage, and promote the revitalization and utilization of agricultural cultural heritage. Not only that, the agricultural cultural heritage comes with regional public brand attributes, long history and its implied unity of mankind, farming culture concept of meticulous cultivation, can become a regional brand of agricultural development of new efficiency points.

(4) Inheritance of farming culture is conducive to strengthening agricultural education and cultivating the three agricultural teams in the new era.

Talent is the mainstay of the inheritance and innovation of traditional farming culture. Entering the new era, the inheritance of farming culture is conducive to reawakening people's awareness of agriculture, enhancing the popularity of agricultural education, guiding the return of laborers, redeeming the declining status of the agricultural economy, and revitalizing the countryside and agriculture.

(5) The inheritance of farming culture is conducive to the implementation of the ecological concept of the unity of man and nature and the improvement of ecological civilization.

In their long-term agricultural practices, Chinese ancestors not only created a splendid farming society, but also formed a farming culture with philosophical implications. The traditional farming culture has always taken the ecological concept of “the unity of man and heaven” as the essence of its thought. The “unity of man and heaven” is an ideal expression of the relationship between heaven, earth and man in traditional societies, which holds that man and nature interact with each other, and emphasizes the rational development and utilization of nature under the premise of harmonious coexistence between man and nature.

The inheritance of farming culture is not only conducive to promoting the development of agriculture, but also capable of passing on the ecological concept of the unity of heaven and man, raising people's awareness of environmental protection and promoting the improvement of ecological civilization.

III. Modeling and solving the cultural resources-task allocation problem

III. A. Linear models

In the algorithmic study of resource allocation problems, the types of cultural resources are usually ignored, i.e., each cultural resource is considered to be used only for a single use, and most of the cultural resources are viewed as multiple one-sided cultural resources. In this case, the dichotomous variable x_{ij} is taken to denote the decision of using the i th $(i=1,\cdots,m)$ cultural resource to the j th $(j=1,\cdots,n)$ allocation goal, and its nonlinear model is shown in equation (1):

$$\begin{gathered} Minimize\sum_{j=1}^{n}V_j\left[\prod_{i=1}^{m}(1-p_{ij}x_{ij})\right]\ Or\ Maximize\sum_{j=1}^{n}V_j\left[1-\prod_{i=1}^{m}(1-p_{ij}x_{ij})\right] \\ Subject\ to\sum_{j=1}^{n}x_{ij}\le 1,\ i=1,\ldots,m \\ x_{ij}\in\{0,1\},\ i=1,\ldots,m,\ j=1,\ldots,n \end{gathered} \tag{1}$$

In the model above, the goal denotes minimizing the survival value of the goal, and constraint 1 is that a cultural resource can only be assigned to at most one goal.

The model (1) is written as an exact linear model based on model (1), again ignoring the type of cultural resources, and the target j is not limited by the number of cultural resources. Assuming m cultural resources and n targets, for any target j each cultural resource i has either assigned or unassigned two states, so there can be 2^m possibilities for each cultural resource to sort the two state combinations of target j, i.e., denote the state of

j by s_j, s_j belongs to $\{0,1,2,cdots,2^m-1\}$, and then the binary state of s_j is used to denote whether the cultural resource i is allocated to j or not by using $bit(s_j,i)$ to denote the value of the i th bit of the binary expression of s_j, $bit(s_j,i)=1$ indicates that i cultural resources are allocated to j targets, and $bit(s_j,i)=0$ indicates that i cultural resources are not allocated to j targets. The symbols in the model are defined as shown in Table 1.

Table 1: The linear model special symbol definition table

s_j	The state of the target j, there are 2^m possibilities, the binary representation.
$bit(s_j,i)$	The variable of 0, 1, the value of the number i bit of s_j binary expression.
x_{j,s_j}	Target j is in s_j state.
q_{j,s_j}	Target function coefficient

The secondary system control table is shown in Table 2. Assuming that there are a total of 3 cultural resources in farming culture (i.e., $m=3$), there are a total of $2^m=8$ possible assigned states for the resource allocation target $j(j=1,\cdots,n)$, and there are 8 possibilities for the value of s_j.

Table 2: The secondary comparison table

Target state s_j (Decimal system)	Target state s_j (binary)	The survival probability p_s of target j
0	000	1
1	001	$1-p_{1j}$
2	010	$1-p_{2j}$
3	011	$(1-p_{1j})(1-p_{2j})$
4	100	$1-p_{3j}$
5	101	$(1-p_{1j})(1-p_{3j})$
6	110	$(1-p_{2j})(1-p_{3j})$
7	111	$(1-p_{1j})(1-p_{2j})(1-p_{3j})$

The variable x_{j,s_j} is used to indicate whether the target j is in the s state, $x_{j,s_j}=1$ means that j is in the s_j state, and $x_{j,s_j}=0$ means that j is not in the s_j state, as shown in the table above. If $x_{1,s_1}=1$ means that target 1 is in state 1 i.e. culture resource 1 hits target 1, then the values of x_{j,s_0}, x_{j,s_2},..., x_{j,s_7} are all 0. Then the linear model of the resource allocation problem can be written as equation (2). where q_{j,s_j} denotes the residual survival probability of j, which can be represented as constraint 3. Constraint 1 restricts each cultural resource to attacking only one target, and constraint 2 restricts each target to taking only one state. The model is equivalent to the second nonlinear model in that the model solution space contains all possible states in which a target is attacked. Therefore its linearization of model (1) is lossless, i.e., it is an exact linear model of model (1):

$$\begin{aligned}
&Minimize\sum_{j=1}^{n}\sum_{s=0}^{2^m-1}q_{j,s_j}x_{j,s_j}\\
&Subject\ to\sum_{j=1}^{n}\sum_{s=0}^{2^m-1}bit(s,i)x_{j,s_j}\leq 1,i=1,\ldots,m\\
&\sum_{s=0}^{2^m-1}x_{j,s_j}=1,j=1,\ldots,n\\
&q_{j,s_j}=V_j\prod_{i=1}^{m}\left[1-bit(s,i)\cdot p_{ij}\right],j=1,\ldots,n\\
&x_{j,s_j}\in\{0,1\},j=1,\ldots,n;s=0,1,\ldots,2^m-1
\end{aligned} \tag{2}$$

III. B. Exact solution methods for linear models

III. B. 1) Column enumeration

Column enumeration is a commonly used method for solving linear programming, to solve the problem of insufficient memory generated by combinatorial explosion. The idea of column enumeration is similar to the column generation method, column enumeration flowchart shown in Figure 1, the specific method is as follows:

First, construct an initial feasible model with a few columns (called the master model), e.g. simply assign the first objective of the allocation of cultural resources for the first purpose, the allocation of the second objective for the allocation of the second objective for the second cultural resource, and so on until all the objectives are allocated cultural resources (when the number of cultural resources is equal to or greater than the target number) or all cultural resources are assigned to the target (when the number of cultural resources is less than the target number).

Then find into the base column. Variables that are important to the current solution in the linear programming model solving process are called base variables, and variables that are not part of the solution are called non-base variables.

Columns that are not in the main model are enumerated, and the pairwise test principle is used on the enumerated columns to test whether their inclusion in the main model would improve the objective value of the problem.

It should be noted that it is not possible to use column generation for the model because if column generation is used then the column generation subproblem must be constructed using model (2), which contains a nonlinear component of column elements. Column enumeration only temporarily solves the out-of-memory problem, but does not save enumeration by any amount. It must be used in conjunction with a pairwise test method to bring the computational effort down significantly.

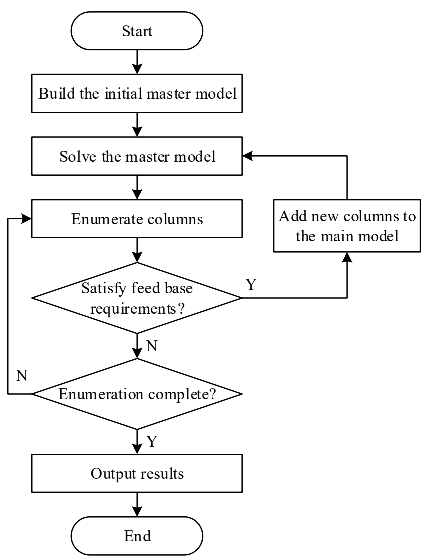

Figure 1: Column enumeration flow chart

III. B. 2) Pairwise tests

The pairwise test is a method used in linear programming solution and sensitivity analysis, for linear programming a variable x_k, assuming that its coefficients in the species of the objective function are c_i, and its vector in the species of the process matrix is a_k, when the objective function is solved to the extreme hours (when it is solved to the maximum hours), the conditions under which the entry of x_k into the base variable may improve the value of the objective function are:

$$\pi_k = c_k - a_k \cdot u < 0 \; (\pi_k = c_k - a_k \cdot u > 0) \tag{3}$$

The u in the above equation is the pairwise solution vector of the current solution.

For model (3), u can be viewed as consisting of two parts. The first part is $[u_1, u_2, \ldots, u_m]^T$, which corresponds to the first constraint of model (2). The second part is $[v_1, v_2, \cdots, v_n]^T$, corresponding to the second constraint of model (2). For $[v_1, v_2, \cdots, v_n]^T$, only v_j can be non-zero in the left equation when the variables are $x_{j,s}$, and so the test condition is:

$$\pi_{js} = q_{js} - \sum_{i=1}^{m} bit(s,i)u_i - v_j < 0,\ j = 1,\cdots,n, s = 0,1,\cdots,2^m - 1 \tag{4}$$

In the above equation, the column $x_{j,s}$ enters the main model only when $\pi_{js} < 0$. According to linear programming theory, as the number of variables in the master model increases, the value of the dyadic solution vector u becomes more and more unfavorable to $\pi_{js} < 0$, and this limits the increase in the size of the master model more and more strongly, i.e., dyadic tests incrementally mitigate combinatorial explosion of the master model.

III. C. Optimization of Solution Algorithm - Genetic Algorithm

In this paper, we design an improved genetic algorithm (L-NSM) incorporating a learning mechanism to promote chromosomes to learn from each other by simplifying the genetic operation and incorporating a learning mechanism to realize efficient evolution of populations.

III. C. 1) Chromosome coding

A chromosome in L-NSM is composed of an ordered arrangement of several villages, denoted as $\chi = (f_1, f_2, \cdots, f_n)$, e.g., $\chi = (3,5,1,4,2)$ means that the first village in village #3 is allocated with a resource, the second village in village #5 is allocated with a resource, and so on. Each village in χ is a gene, and multiple chromosomes make up the population, with the population size being the total number of chromosomes in the population.

III. C. 2) Greedy operator

Since the encoding of chromosomes cannot directly correspond to the solution of the original problem, L-NSM employs a greedy operator to decode the chromosomes to ensure that one chromosome corresponds to a set of feasible solutions. The core logic of the greedy operator is similar to the RBS algorithm, which allocates agro-cultural resources to villages in a sequential order to finalize the overall allocation scheme.

III. C. 3) Genetic manipulation

Traditional crossover and mutation operations are prone to countryside duplication or omission, and the algorithm needs to correct for invalid chromosomes, which increases the complexity of the algorithm. To simplify the genetic operation, L-NSM uses genetic operation based on gene neighbor movement.

The positional distance a village moves forward or backward in the priority sequence is denoted as n_{NM}, and the algorithm presupposes that the maximum neighbor movement distance allowed for each village is denoted as n_{NM}^{max}. If the gene neighbor movement result is generated randomly (NMR), the individual evolution has no direction. To solve the NMR directionless evolution problem, L-NSM introduces a learning mechanism to guide gene neighbor movement (NMG) by constructing an individual evolution score table.

In NMG, the individual evolutionary score table is a score table of size $n \times n$ (n is the number of affected villages). The score table is updated in the algorithm loop with respect to the change in the value of the objective function of an individual. Suppose that in the g-generation score table, the value of the score in the i-row and j-column is $\tau_{i,j}^g$, which denotes the score of countryside i ranked ahead of countryside j. Chromosome χ ranks countryside i before countryside j in generation $g-1$, and countryside j before countryside i after evolution, and the efficiency and fairness objective values of χ before and after evolution are $(\tilde{C}_\chi^{g-1}, \tilde{G}_\chi^{g-1})$ and $\left(\tilde{C}_\chi^g, \tilde{G}_\chi^g\right)$ respectively after normalization. Then, the updates of $\tau_{j,i}^g$ and $\tau_{i,j}^g$ in the gth generation fraction are computed as in Eqs. (5) and (6):

$$\tau_{j,i}^g = \tau_{j,i}^{g-1} + \rho_1\left(\tilde{C}_\chi^{g-1} - \tilde{C}_\chi^g\right) + \rho_2\left(\tilde{G}_\chi^{g-1} - \tilde{G}_\chi^g\right) \tag{5}$$

$$\tau_{i,j}^g = \tau_{i,j}^{g-1} + \rho_1\left(\tilde{C}_\chi^g - \tilde{C}_\chi^{g-1}\right) + \rho_2\left(\tilde{G}_\chi^g - \tilde{G}_\chi^{g-1}\right) \tag{6}$$

where ρ_1 and ρ_2 are weight coefficients satisfying $\rho_1, \rho_2 \in (0,1)$ and $\rho_1 + \rho_2 = 1$. In order to realize that the population can evolve towards both optimization objectives in a balanced way, we can make $\rho_1 = \rho_2 = 0.5$. For the problem where both objectives are minimized, the larger the value of $\tau_{j,i}^g$ indicates that the countryside j is ranked better before the countryside i. Conversely, a smaller value indicates that countryside i ranks better before countryside j.

Further, each chromosome gets a composite score according to the latest score table, which is a summation of the scores of all the relative positional relationships of the villages in the chromosome, e.g., the g th generation chromosome $\chi=(2,4,3,1)$, whose composite score η_{χ}^{g} is computed as in Eq. (7), and the higher the value of the composite score indicates that all the villages in the chromosome are in a relatively location relationship is more favorable. Namely:

$$\eta_{\chi}^{g}=\tau_{2,4}^{g}+\tau_{2,3}^{g}+\tau_{2,1}^{g}+\tau_{4,3}^{g}+\tau_{4,1}^{g}+\tau_{3,1}^{g} \tag{7}$$

To illustrate the NMG genetic operation with an example, let the g th generation chromosome be $\chi=(2,4,3,1)$, the current value of the latest individual evolutionary score, $n_{NM}^{\max}=1$ in the NMG, and randomly selecting the countryside neighboring position of #3 to move, the possible evolutionary outcomes of χ will be either $\chi_1'=(2,3,4,1)$ or $\chi_2'=(2,4,1,3)$. Comprehensive scores are calculated according to Eq. (8) and Eq. (9), and finally, $\chi_{2'}$ with higher scores is selected as the result of NMG genetic manipulation of χ. Namely:

$$\begin{aligned}\eta_{\chi_1'}^{g}&=\tau_{2,3}^{g}+\tau_{2,4}^{g}+\tau_{2,1}^{g}+\tau_{3,4}^{g}+\tau_{3,1}^{g}+\tau_{4,1}^{g}\\&=29-13+20-54+46-37=-9\end{aligned} \tag{8}$$

$$\begin{aligned}\eta_{\chi_2'}^{g}&=\tau_{2,4}^{g}+\tau_{2,1}^{g}+\tau_{2,3}^{g}+\tau_{4,1}^{g}+\tau_{4,3}^{g}+\tau_{1,3}^{g}\\&=-13+20+29-37+54-46=7\end{aligned} \tag{9}$$

III. C. 4) Satisfactory solution selection

For multi-objective optimization algorithms, the results generally contain multiple Pareto solutions, but in practice, the decision maker can only choose one as a satisfactory solution for implementation. In this paper, we use the deviation indicator based on the RBS results, which is calculated as Eqs. (10) and (11):

$$\Delta_f=\begin{cases}C_f^{AC}-C_f^{AC-RBS} & C_f^{AC}>C_f^{AC-RBS}\\ 0 & C_f^{AC}\le C_f^{AC-RBS}\end{cases} \tag{10}$$

$$E=\sum_{f\in F}\Delta_f \tag{11}$$

where C_f^{AC-RBS} is the calibration cost of countryside f in the results of the RBS algorithm. Δ_f is the calibration cost variance of countryside f. E is the total calibration cost deviation. Ultimately, the satisfactory solution to the original problem chooses the Pareto solution that minimizes the total calibration cost deviation.

III. C. 5) Overall Algorithm Flow

The overall process of the improved genetic algorithm incorporating the learning mechanism is as follows:

Step 1: Make g=1, randomly generate the initial population P_g with a population size of $2n_p$ and make all elements of the individual evolutionary score table zero.

Step 2: Calculate the delay and route assignment results for each chromosome in P_g based on greedy operator.

Step 3: Calculate the efficiency and fairness objective of each chromosome in P_g and normalize it.

Step 4: Judge $g>1$, if it is satisfied, update the individual evolutionary score table and go to Step 5. If it is not satisfied, go to Step 5 directly.

Step 5: Calculate the dominance rank and crowding degree of each chromosome in P_g, and keep half of the excellent individuals for the parent population P_g^1.

Step 6: Perform NMG operation on the chromosomes with φ proportion in P_g^1, and perform NMR operation on the remaining chromosomes with $1-\varphi$ proportion, and then merge the new populations generated from the two parts into the offspring population P_g^2.

Step 7: Merge P_g^1 and P_g^2 to form a new generation population P_{g+1}, and determine $g<g_m$ (g_m is the preset maximum number of iterations), if satisfied, make $g=g+1$ and go to Step2. If not, go to Step8 directly.

Step 8: Apply greedy operator to the g_m th generation population to find the delay and route allocation result of each chromosome, calculate the efficiency, fairness objective and chromosome dominance rank, and take the individual with the highest dominance rank as the Pareto frontier solution set.

Step 9: Select the actual satisfactory solution and the algorithm ends.

In order to avoid the imbalance of scores due to the difference of the two objective dimensions, the normalization in Step3 is handled as in Eqs. (12) and (13):

$$\tilde{C}_{\chi}^{g}=\frac{C_{\chi}^{g}-\min_{\chi\in P_g} C_{\chi}^{g}}{\max_{\chi\in P_g} C_{\chi}^{g}-\min_{\chi\in P_g} C_{\chi}^{g}} \tag{12}$$

$$\tilde{G}_{\chi}^{g}=\frac{G_{\chi}^{g}-\min_{\chi\in P_g} G_{\chi}^{g}}{\max_{\chi\in P_g} G_{\chi}^{g}-\min_{\chi\in P_g} G_{\chi}^{g}} \tag{13}$$

IV. Empirical analysis of the allocation of resources to farming culture

IV. A. Genetic Algorithm Optimization Solution

IV. A. 1) Parameter selection

Before comparing the performance of different methods, the crossover rate R_c, the variation rate R_m and the initial number of individuals N of L-NSM should be determined.

The convergence behavior of L-NSM is observed by trials under the throughput model of the fitness function.

In all trials, the values of K, B and F are set to be 60, 6 and 15, respectively. N is set to be 50, R_m=0.3, and R_c varies between 0.2 and 1, with an incremental change of -0.2. The effect of crossover rate on the convergence of the L-NSM is shown in Fig. 2.

After the number of iterations reaches 10, R_c of 0.4 and 1.0 cases have similar convergence behavior. Larger values of the fitness imply that the solution obtained by the L-NSM satisfies the objective function in the throughput model well. That is, the larger the value of the fitness, the better the performance of the L-NSM solution obtained using the given parameters. It can be observed from the figure that when R_c is 0.8, the L-NSM solution performs poorly. The higher crossover rate results in greater computational overhead due to the higher crossover rate.

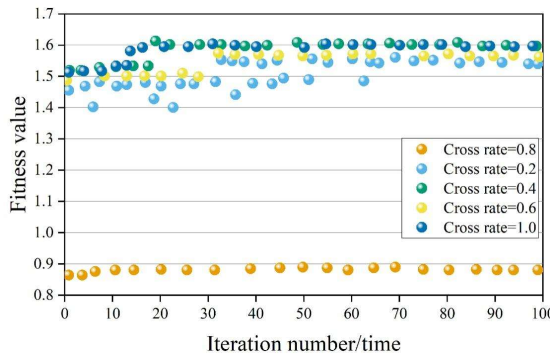

Figure 2: The effect of cross ratio on the convergence of L-NSM

Therefore, in this test R_c is set to 0.4. Setting N=50 and R_c=0.4, the value of R_m is varied from 0.1 to 1.0 with an incremental change of 0.2, and the effect of R_m on the convergence of L-NSM is analyzed. The effect of variation rate on L-NSM convergence is shown in Fig. 3, when R_m is 0.6, the adaptation value is superior, and the variation rate R_m is set to 0.6.

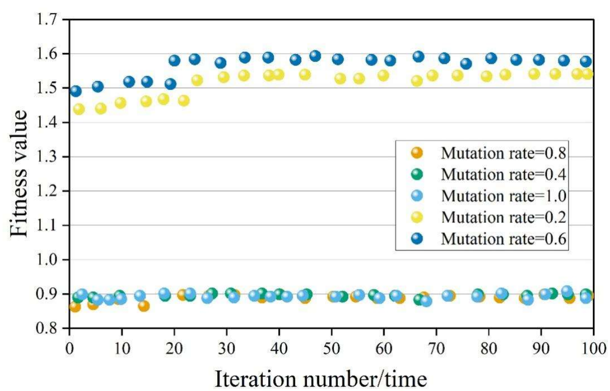

Figure 3: The effect of variation on the convergence of L-NSM

IV. A. 2) Standard test functions

In order to verify the effectiveness of the proposed algorithm (L-NSM) in this paper, the performance of the proposed algorithm will be examined here by using standard test functions.

(1) In this paper, the performance of L-NSM is proved by comparing the results through four standard test functions. The four standard test functions are as follows:

$$ZDT1:\begin{cases} f_1(x)=x_1 \\ f_2(x)=z\left(1-\sqrt{\dfrac{f_1}{z}}\right) \end{cases} \tag{14}$$

where $z=1+\dfrac{9\sum_{l=2}^{k}x_l}{k-1}$, $x_l\in[0,1]$, $l=1,2,\ldots,30$, and k is the dimension of the search space.

$$ZDT2:\begin{cases} f_1(x)=x_1 \\ f_2(x)=z\left(1-\dfrac{f_1}{z}\right)^2 \end{cases} \tag{15}$$

where $z=1+\dfrac{9\sum_{l=2}^{k}x_l}{k-1}$, $x_l\in[0,1]$, $l=1,2,\ldots,30$, and k is the dimension of the search space.

$$ZDT3:\begin{cases} f_1(x)=x_1 \\ f_2(x)=z\left[1-\sqrt{\dfrac{f_1}{z}}-\dfrac{f_1}{z}\sin(10\pi f_1)\right] \end{cases} \tag{16}$$

where $z=1+\dfrac{9\sum_{l=2}^{k}x_l}{k-1}$, $x_l\in[0,1]$, $l=1,2,\ldots,30$, and k is the dimension of the search space.

$$ZDT6:\begin{cases} f_1(x)=1-\exp(-4x_1)\sin^6(6\pi x_1) \\ f_2(x)=z\left[1-\left(\dfrac{f_1}{z}\right)^2\right] \end{cases} \tag{17}$$

where $z=1+9\left[\dfrac{1}{k-1}\sum_{l=2}^{k}x_l\right]^{0.25}$, $x_l\in[0,1]$, $l=1,2,\ldots,10$, and k is the dimension of the search space.

The ideal Pareto Front of the test function chosen in this paper. The ideal PF of ZDT1 is a convex curve, the ideal PF of ZDT2 is a concave curve, the ideal PF of ZDT3 is a discrete curve, and the ideal PF of ZDT16 is a concave curve.

(2) The optimal solutions obtained from the test functions are subjected to the following performance evaluations: distributivity and approximation evaluation metrics to evaluate the superiority of the solutions.

Distributability evaluation: characterize the distance of each neighboring solution in the set of optimal solutions obtained from optimization, which is defined as follows:

$$S=\frac{1}{n-1}\sum_{i=1}^{n}\left(\overline{d}-d_i\right)^2 \tag{18}$$

There are a total of n elements within the optimal solution set, i and j are two of them, and the smaller the value of the spacing S, the better the dispersion of the solution.

Approximation evaluation: indicates the distance between the optimal solution in the set of optimal solutions obtained from optimization and the true optimal solution of the problem, which is defined as follows:

$$D=\left[\ddot{f}(X)-\ddot{f}_{true}(X)\right] \tag{19}$$

The smaller the value of the distance D, the better the approximation of the solution.

IV. A. 3) Experimental results

(1) Test 1

The performance of the improved algorithm is judged by the given evaluation criterion IGD, and in order to be able to more accurately reflect the performance of the algorithm, the NSGA-II algorithm and the Multiobjective Particle Swarm Algorithm MOPSO are used as comparison algorithms. Where the number of data in the rational $PE\left(P^{'}\right)$ in the IGD is 1000, the smaller the value of the IGD, the better the quality of the solution of the PF found.

In order to effectively verify the effectiveness of the algorithms, the same running parameters are set for all the algorithms, and the following running parameters are set: population size: 180, hybridization probability: 0.4, mutation probability: 0.6, and the maximum number of iteration generations of the population: 1000. In order to reduce the error during the running process and improve the reliability of the running results, each test function is run independently for 60 times, and the most typical running results are recorded once.

The results of the ZDT1 experiment are shown in Fig. 4. From the figure, it can be seen that the MOPSO algorithm has a larger IGD value when running independently, and the best IGD value of MOPSO algorithm is 0.01123, which indicates that MOPSO algorithm does not have an advantage in the performance here.The best IGD value of L-NSM algorithm is 0.00732.

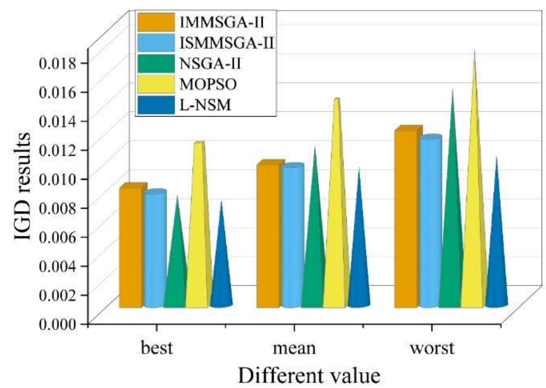

Figure 4: ZDT 1 experimental results

The results of ZDT2 experiments are shown in Fig. 5.The MOPSO algorithm and L-NSM algorithm IGD values are similar in ZDT2 experiments, and the optimal IGD values are 0.00472 and 0.00450, respectively.

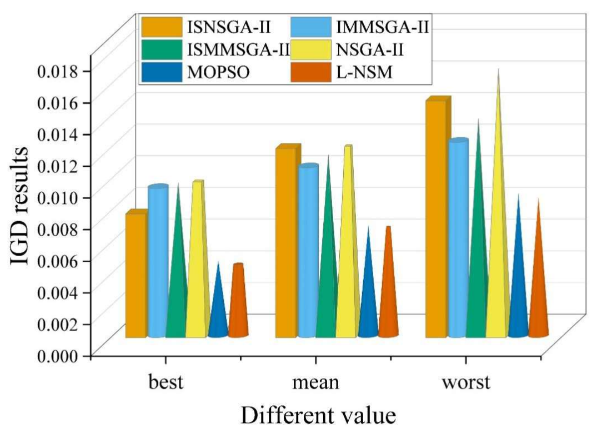

Figure 5: ZDT 2 experimental results

The results of ZDT3 experiments are shown in Fig. 6.The optimal, mean, and maximum values of the L-NSM algorithm are 0.00876, 0.01102, and 0.01238, respectively.Compared with the IMMSGA-II algorithm, the optimal, mean, and maximum values differ by 0.00222, 0.00103, and 0.00233, respectively.

The results of ZDT6 experiments are shown in Fig. 7. It can be clearly seen that the MOPSO algorithm has a larger IGD value and poor algorithm performance in the ZDT6 experiments. While L-NSM algorithm has better IGD index performance in ZDT1, ZDT2, ZDT3 and ZDT6 experiments. Multiple experiments verify the universality of the L-NSM algorithm.

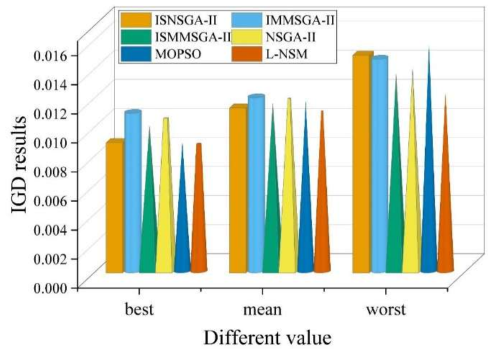

Figure 6: ZDT 3 experimental results

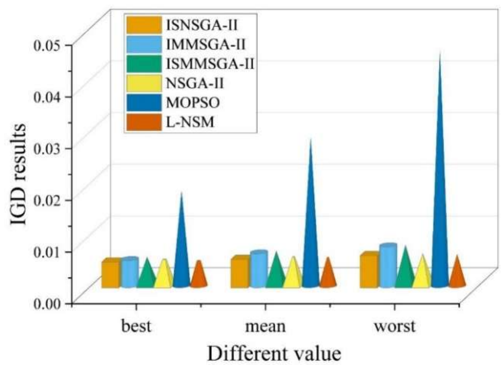

Figure 7: ZDT 6 experimental results

(2) Test 2

When α = 1.0, the comparative analysis results of different algorithms are shown in Table 3. Comparing the experimental data of the two algorithm evaluation indexes of distributivity evaluation (S) and approximation evaluation (D), the overall performance of the L-NSM algorithm in optimization searching is superior to other algorithms, which indicates the effectiveness of the L-NSM algorithm.

Table 3: Comparison analysis of different algorithms

Index	Method	Pro1	Pro2
S	ISNSGA-II	9.6325	1.6385
D		6.6364	0.5263
S	IMMSGA-II	9.2078	1.7859
D		5.9683	0.6011
S	ISMMSGA-II	8.9621	1.5243
D		5.6369	0.4668
S	NSGA-II	8.8225	1.4253
D		5.5136	0.5263
S	MOPSO	9.0213	1.7907
D		5.5510	0.4913
S	L-NSM	7.8951	1.4197
D		5.2798	0.4551

When α = 0.5, the statistics of the comparison results of multiple algorithms are shown in Table 4. Comparing the various algorithms in the table, the distributional and approximation evaluation values of MOPSO algorithm under Pro1 are 8.1189 and 4.0423, respectively. Except for L-NSM algorithm, MOPSO algorithm achieves a good performance in the distributional and approximation evaluations when α is taken as 0.5.

Table 4: When α = 0.5, the comparison results of multiple algorithms are calculated

Index	Method	Pro1	Pro2
S	ISNSGA-II	8.8962	1.2525
D		5.5636	0.3659
S	IMMSGA-II	8.9817	1.3678
D		5.6693	0.4014
S	ISMMSGA-II	8.5501	0.8694
D		4.2361	0.2316
S	NSGA-II	8.4028	0.8505
D		4.0003	0.2496
S	MOPSO	8.1189	0.7118
D		4.0423	0.3251
S	L-NSM	7.9686	0.5424
D		4.0213	0.2365

When α = 0.1, the statistics of the comparison results of the six algorithms are shown in Table 5.Under Pro2, the evaluation values of the L-NSM algorithm's distributivity and approximation are 1.0763 and 0.1028, respectively.Combining the data of each algorithm in the table, the L-NSM algorithm's overall performance of optimization is more advantageous to a certain extent.

Table 5: When the α = 0.1, the comparison of the six algorithms is counted

Index	Method	Pro1	Pro2
S	ISNSGA-II	6.2639	1.0253
D		3.5874	0.1189
S	IMMSGA-II	6.6550	1.0396
D		3.6989	0.1426
S	ISMMSGA-II	6.1215	1.1556
D		3.2357	0.1339
S	NSGA-II	6.1586	1.1758
D		3.2634	0.2364
S	MOPSO	5.8967	1.0805
D		2.9869	0.1136
S	L-NSM	5.5786	1.0763
D		2.6361	0.1028

IV. B. Empirical analysis

Farming culture refers to a kind of customs and culture formed by farmers in long-term agricultural production. Southern Shaanxi has a long history and culture, in the Stone Age the ancestors have been engaged in agricultural development here, is one of the earlier agricultural origins of the region. The unique natural environment and complex geographical conditions have created rich agricultural resources in southern Shaanxi.

Among them, Hanzhong City has characteristic high-quality agricultural resources, including green vegetables, citrus, rice, tea, edible fungi, Chinese herbs, chicken, hogs and so on. Yangxian black rice, Yangxian red rice, Luoyang dulcimer, Hanzhong Xianhao, Chenggu honey tangerine, Hanzhong giant salamander, Hanzhong epimedium, Hanzhong white pig and other geographical indication products. At the same time, Hanzhong City has Qingmuchuan Ancient Town, Liuhou Ancient Town, Zhuge Ancient Town, Huayang Ancient Town, Shangyuan Guan Ancient Town, Luojiaba Ancient Town, Qingshu Ancient Town, Mizi Ancient Town, Baoguo Ancient Town and other tourist towns, which are rich in resources of farming ecological culture and tourist towns. In this paper, a rural revitalization cooperative department in Hanzhong City is selected as a research object to analyze the optimization allocation efficiency of farming culture resources in this rural revitalization department.

IV. B. 1) Data collection

In this paper, through field research and data collection and screening of D rural revitalization cooperative department, the allocation of farming cultural resources in the daily rural revitalization strategy work of the cooperative department in 2020-2024 is counted.

Through the arrangement and classification of the data, the basic data of the daily farming cultural resources input of this rural revitalization cooperative department are obtained.The basic data of the farming cultural resources input of the rural revitalization cooperative department of D from 2020 to 2024 are shown in Table 6.

The inputs of farming cultural resources under the rural revitalization strategy work are divided into personnel resources, material resources, environmental resources and management resources. For environmental resources, subdivided into natural environment and specific environment, the input data in 2024 are 50.1134 and 49.1027, respectively. 2024 for the management of farming cultural resources to focus on arrangements, its input data is 65.0709.

Table 6: The department's agricultural cultural resources are invested in basic data

Dimension		2020	2021	2022	2023	2024
Personnel resources	Technical proportion	0.5124	0.4993	0.4779	0.5326	0.5124
	Skill training	0.4869	0.4362	0.3898	0.3978	0.4233
Material resources	The level of agricultural culture	52.5261	46.8799	41.0055	40.2859	49.3674
	Inheritance of agricultural culture	3.8803	2.2968	2.9017	2.2347	2.8936
Environmental resources	Natural environment	54.6365	54.8695	43.7586	48.9668	50.1134
	Specific environment	56.3240	49.5286	38.5476	46.7759	49.1027
Managerial resources	Task allocation	70.6631	65.8879	68.5579	61.4432	65.0709
	Resource allocation efficiency	0.5263	0.4586	0.5213	0.5078	0.5263

IV. B. 2) Analysis of results

In order to eliminate the problem of not being able to make direct comparative analysis caused by the inconsistency of the base data's scale, it is necessary to standardize the base data of the farming culture resources of D rural revitalization cooperative sector from 2020 to 2024. In this paper, the base data are processed by means of homogenization transformation.

By substituting the collected data into the linear programming model of farming cultural resource allocation in D rural revitalization cooperative sector, the optimization model of farming cultural resources in this rural revitalization cooperative sector can be obtained. The objective function and constraints are formulated, and the L-NSM algorithm is applied to calculate the above resource optimization model, and after 91 iterations, the approximate optimal solution of the model is finally obtained as 85.0027.

Since the units of each resource indicator are different, the data of resource indicators are expressed uniformly according to the score for the convenience of the study.The optimization comparison of the data related to the management resources of D Rural Revitalization Cooperative sector in 2023-2024 is shown in Figure 8.

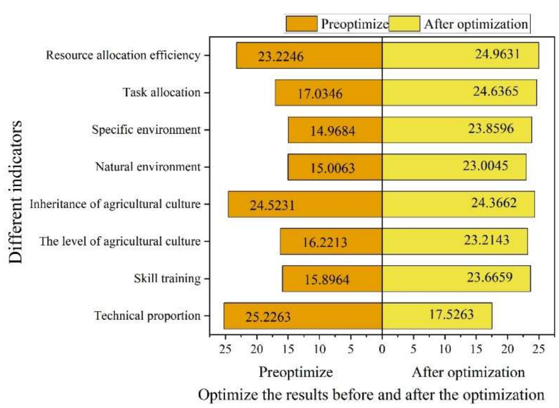

Figure 8: The optimization comparison of the management resource related data

From the results of the resource allocation comparison before and after the optimization of the farming culture resource allocation in the D rural revitalization cooperative sector in 2024, it can be seen that: before the optimization, the combination of management resource inputs in terms of the proportion of technical staff, skill training, level of farming culture resources, farming culture resource inheritance, the natural environment, the specific environment, the task allocation and the efficiency of the resource allocation in this rural revitalization cooperative sector is (25.2263, 15.8964, 16.2213, 24.5231, 15.0063, 14.9684, 17.0346, 23.2246). At this time, the farming culture resource allocation capacity of this rural revitalization cooperative sector is 68.9423. The optimized combination of each key resource input according to the linear planning model of optimal resource allocation is (17.5263, 23.6659, 23.2143, 24.3662, 23.0045, 23.8596, 24.6365, 24.9631). At this point, the resource allocation capacity of this rural revitalization cooperative sector for farming culture has increased to 85.0027, which meets the required standard of higher resource allocation capacity for farming culture in this rural revitalization cooperative sector.

V. Conclusion

In this paper, we statistically organize the input data of farming cultural resources under the implementation of rural revitalization strategy, establish a linear planning model for optimal allocation of resources, and use the improved genetic algorithm with fusion learning mechanism to solve the linear planning model for the allocation of farming cultural resources.

(1) In order to test the population efficiency of the improved genetic algorithm of the fusion learning mechanism, the experimental results were obtained with a crossover rate of 0.4, a variance rate of 0.6, and an initial number of individuals of 50. Standard test function tests were carried out with other algorithms, and in the series of experiments of the ZDT, the IGD values of the improved genetic algorithm of the fusion learning mechanism were all the smallest. And when α takes the value [0.1,1.0], the algorithm all has the optimal distributional evaluation efficiency and approximation evaluation efficiency. It indicates that the genetic algorithm improved by using the learning mechanism has the feasibility of further operation in the model solving of the resource optimization allocation problem.

(2) There is a gap of 16.0604 in the resource allocation capacity before and after the optimization of this rural revitalization cooperative department, which indicates that the linear planning model of optimal resource allocation established by the input data of farming cultural resources consisting of personnel resources, material resources, environmental resources and management resources can optimize the allocation of farming cultural resources.

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