Regional Science and Technology Resource Allocation Optimization Based on Improved Genetic Algorithm

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Abstract

With the advent of the knowledge economy, science and technology resources have played an important role in economic competition, and their optimal allocation has been regarded as very important across the world. Thus, allocation optimization research for regional science and technology resources is significant for accelerating the reform of regional science and technology systems. Regional science and technology resource allocation optimization is modeled as a double-layer optimization model: the entire system is characterized by top-layer optimization, whereas the subsystems are characterized by bottom-layer optimization. To efficaciously solve this optimization problem, we propose a mixed search method based on the orthogonal genetic algorithm and sensitivity analysis. This novel method adopts the integrated modeling concept with a combination of the knowledge model and heuristic search model, on the basis of the heuristic search model, and simultaneously highlights the effect of the knowledge model. To compare the performance of different methods, five methods and two channels were used to address an application example. Both the optimized results and simulation time of the proposed method outperformed those of the other methods. The application of the proposed method to solve the problem of entire system optimization is feasible, correct, and effective.

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1. Introduction

Regional autonomous innovation is defined as the most innovative individuals (e.g., enterprises, colleges, and institutions) independently solving the major technical problems in the social and economic development process through original innovation and integrated innovation [1-3]. Scientific and technological resources are various resource factors that directly act on scientific research and technological innovation, including scientific and technological human resources, scientific and technological inputs, scientific and technological infrastructures, and natural scientific and technological resources [4-5]. These are the foundation and precondition of creating scientific and technological achievements. Only the rational allocation of scientific and technological resources as the primary productive force promoting regional autonomous innovation can ensure the vigor of regional innovation [6-8].

At present, China has some problems regarding scientific and technological resource allocation, such as insufficient input scale, imbalanced local structure, and serious allocation administration [9-11]. Because of the liquidity and space root of scientific and technological resources, based on the resource allocation principle, scientific and technological resource allocation refers to the organization of various scientific and technological resources in different innovation fields, subjects, processes, and spaces according to social development requirements [12-13]. The main allocation modes include government-based plan allocation and market-based market allocation.

The government allocates scientific and technological resources through directly investing in research and development activities, and formulating corresponding policies, systems, laws, and regulations; however, this mode lacks market demand orientation. It is not the optimal mode to promote regional autonomous innovation development [14-15]. The market-based market allocation mode positively reflects the market demand of scientific and technological resources, but the information asymmetry of the technology market ultimately results in a rise in the cost of scientific and technological resource allocation and a decrease in efficiency. It is also not the optimal mode of scientific allocation of scientific and technological resources.

Therefore, the present research proposes a ‘government-market,’ which is a different joint allocation mode from the perspective of regional scientific and technological resource gathering. According to the features of regional innovation and a combination of the types of scientific and technological resources and allocation efficiency, the government regards regional scientific and technological resource superiority and weaknesses, the balanced relationship between scientific research institutions and enterprises and market demand is an important reference to scientifically guide scientific and technological resource flow to give play to their value and achieve ‘government-market’ different joint allocation mode of regional scientific and technological resources.

2. Problem Formulation

A regional science and technology resource allocation system demonstrates a high level of integration with respect to certain requirements, and consists of various subsystems that are functionally interrelated and interacting, with the characteristics of wholeness, diversity of internal composition, and multilevel and comprehensive integration. The base layer subsystems can be developed individually, and the proposed system can both use and control these subsystems. The individuality and interdependence among subsystems is subject to the designers and developers of the entire system. In the condition of modern society, the optimization of regional science and technology resources not only depends on one certain type or certain types of subsystems, but also relies on the entire system determined by all the subsystems and whether it can be appropriately applied in practice. To solve the short slab and bottleneck problem of a regional science and technology resource allocation system, it is necessary to evaluate and optimize its capability to adapt to modern society.

Hypothesis 1: The performance of a regional science and technology resource allocation system depends on the integrated performance of its subsystems [16] (e.g., research and development organization of enterprises, educational institution, and scientific institution).

Hypothesis 2: The performance of the subsystems of the regional science and technology resource allocation system depends on different evaluation indicators [16] (e.g., input of human resources, input of financial resources, input of physical resources, input of information resources, and input of organization resources).

According to the above hypothesizes, the regional science and technology resource allocation optimization problem can be explained as **Fig. 1**. For each subsystem, it is very difficult to describe the relationship between evaluation indicators and performance indices using mathematical functions; similarly for the entire system. Thus, the simulation model is applied to characterize the relationship between evaluation indicators and performance indices of the subsystem and entire system. Regional science and technology resource allocation optimization can be summarized as follows: by adopting simulation optimization approaches in the resource allocation system, obtain the near-optimum solution or optimum solution.

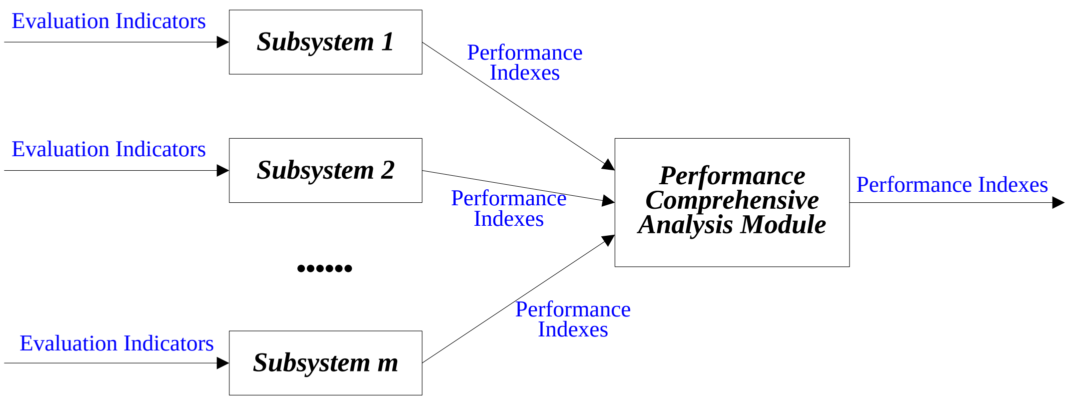

Fig. 1. Regional science and technology resource allocation optimization

Suppose that $P_1, P_2, ..., P_s$ denote some performance index that requires the maximization of the proposed system and $Q_1, Q_2, ..., Q_r$ denote some performance index that requires the minimization of the proposed system. These performance index values can be acquired through the whole simulation implementation of the regional science and technology resource allocation system:

$$P_i = Sim\left(S_1, S_2, ..., S_\lambda\right),\ i = 1, 2, ..., s\ , \tag{1}$$

$$Q_i = Sim\left(S_1, S_2, ..., S_\lambda\right),\ i = 1, 2, ..., r\ , \tag{2}$$

where Sim indicates that the relationship between the input and output is symbolized by a simulation model and $S_i (1 \le i \le \lambda)$ denotes the simulation output of the i^{th} subsystem, and λ denotes the number of subsystems in the proposed system. Let T denote the total consumption time of the whole simulation optimization process:

$$T = \sum_{i=1}^{\lambda+1} t_i \times c_i\ , \tag{3}$$

where $t_i (1 \le i \le \lambda)$ denotes the average simulation time of running the i^{th} subsystem, $t_{\lambda+1}$ denotes the average time of computing the performance comprehensive analysis module, $c_i (1 \le i \le \lambda)$ denotes the total times of running the i^{th} subsystem, and $c_{\lambda+1}$ denotes the total times of computing the performance comprehensive analysis module. Each subsystem of the entire system is symbolized by a simulation model:

$$S_i = Sim\left(x_{i1}, x_{i2}, ..., x_{i(k_i)}\right),\ i = 1, 2, ..., \lambda\ , \tag{4}$$

where $x_{ij} = (i = 1, 2, ..., \lambda;\ j = 1, 2, ..., k_i)$ denotes the j^{th} input variable of the i^{th} subsystem, k_i denotes the number of input variable in the i^{th} subsystem. Let x_{ij}^{low} and x_{ij}^{up} denote the lower bound and upper bound of input variable x_{ij}, then $x_{ij} \in [x_{ij}^{low}, x_{ij}^{up}]$. Let n denotes the total number of the whole system, then $n = \sum_{i=1}^{\lambda} k_i$.

A simple example is displayed to understand the proposed problem (see **Fig. 2**). In this example, P_1 denotes the performance index that requires the maximization of the proposed system, and

$$P_1 = Sim\left(S_1, S_2\right).$$

Q_1 and Q_2 denote the performance index that requires the minimization of the proposed system, and

$$Q_1 = Sim\left(S_1, S_2\right),$$

$$Q_2 = Sim\left(S_1, S_2\right).$$

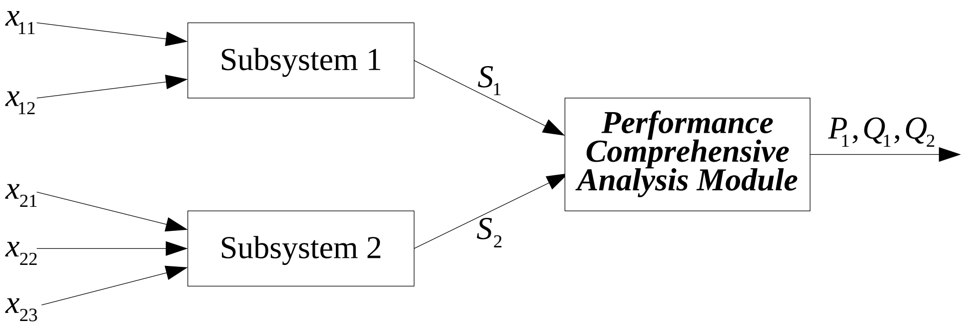

Fig. 2. A simple example of the proposed problem

Here,

$$S_1 = Sim\left(x_{11}, x_{12}\right),$$

$$S_2 = Sim\left(x_{21}, x_{22}, x_{23}\right).$$

Suppose that t_1 and t_2 denote the average simulation time of running the first subsystem and the second subsystem respectively, and t_3 denotes the average time of computing the performance comprehensive analysis module. Let c_1 and c_2 denote the total times of running the first subsystem and the second subsystem respectively, and c_3 denotes the total times of computing the performance comprehensive analysis module. In this simple example, the total consumption time of the whole simulation optimization process is

$$T = \sum_{i=1}^{3} t_i \times c_i \ .$$

Suppose that the feasible space of input variable $x_{ij} \in [-5, 5], i = 1, 2; j = 1, 2, \cdots, k_i$. Here, $k_1 = 2, k_2 = 3$.

In conclusion, the mathematical model of the simulation optimization of the regional science and technology resource allocation system can be formulated as follows:

$$\begin{cases} \max\left\{P_1, P_2, ..., P_s\right\} \\ \min\left\{T, Q_1, Q_2, ..., Q_r\right\} \end{cases}$$

$$s.t. \begin{cases} P_i = Sim\left(S_1, S_2, ..., S_\lambda\right), \ i = 1, 2, ..., s \\ Q_i = Sim\left(S_1, S_2, ..., S_\lambda\right), \ i = 1, 2, ..., r \\ T = \sum_{i=1}^{\lambda+1} t_i \times c_i \\ S_i = Sim\left(x_{i1}, x_{i2}, ..., x_{i(k_i)}\right), \ i = 1, 2, ..., \lambda \\ x_{ij} \in \left[x_{ij}^{low}, x_{ij}^{up}\right], \ i = 1, 2, ..., \lambda; \ j = 1, 2, ..., k_i \end{cases} \tag{5}$$

If regional science and technology resource allocation optimization is studied as a whole, the optimization efficiency is certain to be lower because of reasons such as an overlarge space of input variables and optimization involving multiple objectives. In addition to whether the near-optimum can be obtained, the huge consumption of the simulation time would make the entire optimization unworkable. Therefore, the authors adopt the multilevel optimization method to accomplish regional science and technology resource allocation optimization.

The mathematical model of top-layer optimization is

$$\begin{cases} \max\{P_1, P_2, ..., P_s\} \\ \min\{T, Q_1, Q_2, ...Q_r\} \end{cases}$$
$$s.t.\begin{cases} P_i = Sim(S_1, S_2, ..., S_\lambda),\ i = 1, 2, ..., s \\ Q_i = Sim(S_1, S_2, ..., S_\lambda),\ i = 1, 2, ..., r \\ T = t_{\lambda+1} \times c_{\lambda+1} \\ S_i \in \left[S_i^{low}, S_i^{up}\right],\ i = 1, 2, ..., n \end{cases} \tag{6}$$

Without considering the details of each subsystem, top-layer optimization attempts to apply the shortest time of the simulation to acquire near-optimum input and output values of regional science and technology resource allocation optimization. Suppose that the near-optimum output value is $(P_1^*, P_2^*, ...P_s^*, Q_1^*, Q_2^*, Q_r^*)$, then the optimization objective of (5) is to determine the optimum input value $(S_1^*, S_2^*, ..., S_n^*)$ in the shortest simulation time that makes the output value equal $(P_1^*, P_2^*, ...P_s^*, Q_1^*, Q_2^*, Q_r^*)$. After such operations, the problem dimension is greatly decreased, and this can effectively reduce the solving complexity.

Bottom-layer optimization aims at every subsystem. For example, consider the i^{th} subsystem. Its optimization model is

$$\min\{T, | S_i - S_i^*\}$$
$$s.t.\begin{cases} T = t_i \times c_i \\ S_i = Sim\left(x_{i1}, x_{i2}, ..., x_{i(k_i)}\right) \\ x_{ij} \in \left[x_{ij}^{low}, x_{ij}^{up}\right],\ j = 1, 2, ..., k_i \end{cases} \tag{7}$$

After the completion of the optimization of the system layer, each subsystem is provided with an optimum output $S_i^*(1 \le i \le n)$. The target of bottom-layer optimization is to seek the best input value $(x_{i1}^*, x_{i2}^*, ..., x_{ik_i}^*)$ of subsystems in the shortest simulation time that makes the output the best value $S_i^*(1 \le i \le n)$ given by top-level optimization.

3. Improved Genetic Algorithm

For the optimization of complex systems, many scholars have used different approaches, for example, the adaptive genetic algorithm [17-18], improved genetic algorithm [19-21], and multi-objective genetic algorithm [22-23]. In particular, Bi proposed an improved genetic algorithm that was designed by incorporating domain knowledge for the water distribution system [24]. Lin proposed a non-dominated sorting genetic algorithm using a gene-therapy method for multi-objective optimization [25].

The increased efficiency of simulation optimization largely depends on the search technique adopted in the optimization process. To a certain extent, the existing search algorithm implicitly attaches the domain knowledge of the optimization problem to the algorithm without the excavation, storage, and application of related domain knowledge that is directly in abundance. As a result, the optimum solution of the optimization problem cannot be obtained most effectively. In this paper, we propose a mixed search method based on the orthogonal genetic algorithm and sensitivity analysis, which adopts the integrated modeling concept with a combination of the knowledge model and heuristic search model, on the basis of the heuristic search model, and simultaneously highlights the effect of the knowledge model (see **Fig. 3**). Then we optimize the organization and complement the advantages with the aforementioned two models to improve the efficiency of the heuristic search technique. The fundamental process of the proposed improved genetic algorithm is shown in **Fig. 3**.

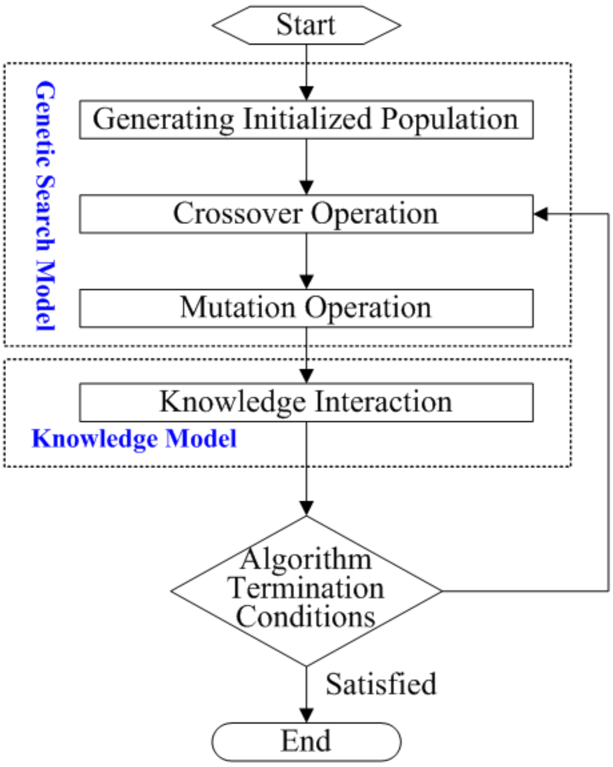

Fig. 3. Optimization architecture of the improved genetic algorithm

3.1 Generating the Initialized Population

The feasible space is divided according to the variable, with the maximum gap between its lower bound and upper bound. Divide the feasible space $[L,U]$ of optimization problems into B subspaces according to the following formula:

$$u_k - l_k = \max_{1 \le i \le n}\{u_i - l_i\}$$
$$\begin{cases} L_i = L + (i-1)[(u_k - l_k)/B]1_k \\ U_i = U + (B-i)[(u_k - l_k)/B]1_k \end{cases} \quad i = 1, 2, ..., B \tag{8}$$

where $L = [l_1, l_2, ..., l_n]^T$ and $U = [u_1, u_2, ...u_n]^T$ denote the lower bound and upper bound of n independent variables, respectively, B denotes the design parameter, 1_k denotes an n dimension column vector with k^{th} digit 0 and the other digits 1, and L_i and U_i denote an n dimension column vector. The feasible space $[L,U]$ is divided into B subspaces $[L_1,U_1],[L_2,U_2],...,[L_B,U_B]$.

Discretize each independent variable in each subspace according to

$$a_{ij} = \begin{cases} l_i & j = 1 \\ l_i + (j-1)[(u_i - l_i)/(Q_i - 1)] & 2 \le j < Q_1 \\ u_i & j = Q_1 \end{cases} \tag{9}$$

Suppose the definition domain of independent variable x_i is $[l_i, u_i]$, as per design parameter Q_1 (odd number), then quantize independent variable x_i as Q_1 levels $a_{i1}, a_{i2}, ..., a_{iQ_1}$.

Select M_1 chromosomes from every subspace. First, construct an orthogonal table $L_{M_1}(Q_1^N) = [a_{ij}]_{M_1 \times N}$, where N denotes the dimension of the optimized problem, $M_1 = Q_1^{J_1}$, and J_1 denotes the positive integer that meets constraint $\frac{Q_1^{J_1} - 1}{Q_1 - 1} \ge N$. Then select M_1 combinations from Q_1^N , and finally produce M_1 chromosomes by the application of these M_1 combinations.

In accordance with the relative merits of the fitness value, choose G optimal chromosomes as the initial population among the M_1B possible chromosomes that have been produced, where G implies the size of the initialized population. More Details of initial population generation can refer to [29].

3.2 Crossover Operation

Select two parent chromosomes for a crossover operation based on the crossover probability. Assume that the two parent individuals in the crossover operation are $\begin{cases} p_1 = (p_{11}, p_{12}, ..., p_{1N}) \\ p_2 = (p_{21}, p_{22}, ..., p_{2N}) \end{cases}$ and define their solution space $[l_{parent}, u_{parent}]$ as

$$l_{parent} = \begin{bmatrix} \min(p_{11}, p_{21}) \\ \min(p_{12}, p_{22}) \\ ... \\ \min(p_{1N}, p_{2N}) \end{bmatrix}^T, \tag{10}$$

$$u_{parent} = \begin{bmatrix} \max(p_{11}, p_{21}) \\ \max(p_{12}, p_{22}) \\ \dots \\ \max(p_{1N}, p_{2N}) \end{bmatrix}^T . \tag{11}$$

It is, each element in l_{parent} is the minimum between the elements in p_1 and p_2 correspondingly, while each element in u_{parent} is the maximum between the elements in p_1 and p_2 correspondingly.

Discretize solution space $[l_{parent}, u_{parent}]$ of the two parent individuals as Q_2 portions (design parameter). Based on the domain knowledge of the optimization, select a partial independent variable that requires the crossover operation. To avoid evaluating the population point in the crossover process on a large scale, every pair of parents produces as few potential descendants as possible. Therefore, the crossover operation in this paper just points at F (design parameter, $1 \le F \le N$) genes (independent variables) of the parent chromosomes. Proceeding without obtaining domain knowledge of the optimized problems, randomly select F gene positions of the same probability; otherwise, according to the probability provided by domain knowledge, stochastically choose F gene positions. Eventually, discretize these F independent variables in each subspace (9).

Select a possible descendant point from the parent solution spaces with the application of the orthogonal table. Produce an orthogonal table $L_{N_2}(Q_2^F) = [b_{ij}]_{M_1 \times F}$, where Q_2 is one odd number, $M_2 = Q_2^{J_2}$, and J_2 is the smallest positive integer that meets constraint $\frac{Q_2^{J_2} - 1}{Q_2 - 1} \ge F$. Select M_2 combinations from Q_2^F combinations, and ultimately generate M_2 possible descendants with the application of these M_2 combinations. With regard to every possible descendant, the selected F genes are valued according to the corresponding level in the orthogonal table, and other genes are selected randomly from the corresponding genes of the parent chromosomes.

Select two individuals with the best fitness value from M_2 possible descendant individuals and two parent individuals as the results of this crossover operation. If the present times of the crossover operation reach the preset value, stop the crossover operation.

3.3 Mutation Operation

Randomly select a parent chromosome based on the mutation probability. Taking into account the domain knowledge of optimized problems, select a certain independent variable. Before obtaining domain knowledge, stochastically select one gene position of the same probability; otherwise, according to the probability offered by domain knowledge, randomly choose one gene position.

Based on the perturbation method, obtain the descendant chromosome after mutation. The perturbation method refers to perturbing selected genes of the parent chromosome as the original $1-2\sigma$, $1-\sigma$, $1+\sigma$, and $1+2\sigma$, where σ is a design parameter, then four descendant chromosomes can be obtained. Select the best individual as result of this mutation from the parent and descendant chromosomes. If the present time of the mutation operation reaches the preset value, stop the mutation operation.

3.4 Knowledge Interaction

Select five solutions that are the nearest to the current optimum solution based on

$$DIS(i, j) = \sum_{k=1}^{N} (x_{ik} - x_{jk})^2 , \tag{12}$$

where $DIS(i, j)$ denotes the distance between solutions i and j, N denotes the dimension of the optimized problem, and x_{ik} and x_{jk} denote the k^{th} independent variable of solutions i and j, respectively, $1 \le k \le N$.

Calculate the sensitivity level (domain knowledge of the optimization problems) of each independent variable to comprehensive performance (synthesis value of multiple targets based on

$$SEN(i) = \frac{\sum_{k=1}^{5} [(y^* - y_k) / (x_i^* - x_{ki})]}{5} , \tag{13}$$

where $SEN(i)$ denotes the sensitivity level of the i^{th} independent variable to comprehensive performance, $y*$ denotes the integrated performance of the present optimum solution, $y_k (1 \le k \le 5)$ denotes the integrated performance of the k^{th} solution that is closest to the present optimum solution, x_i^* denotes the i^{th} independent variable value of the present optimum solution, and x_{ki} denotes the i^{th} independent variable value of the i^{th} solution that is closest to the present optimum solution.

With the use of explored domain knowledge to guide the following optimization process, calculate the operated probability of every independent variable in the following optimization process based on

$$Pr_i = SEN(i) / \sum_{i=1}^{N} SEN(i) , \tag{14}$$

where Pr_i denotes the operated probability of the i^{th} independent variable, $SEN(i)$ implies the sensitivity level of the i^{th} independent variable to integrated performance, and N indicates the dimension of the present optimization problems. In the following optimization process, each independent variable is a selected operation according to probability Pr_i.

3.5 Algorithm Termination Conditions

If the present optimization situation meets the algorithm termination conditions, then stop the optimization; otherwise, consider the crossover operation. The algorithm termination condition in this paper is defined as follows: if the relative error between the present optimum solution and expected (known) optimum solution is less than 0.5%, then the optimization process ends (if the expected optimum is known); if the total iteration times are larger than 500, then the optimization process ends (if the expected optimum is unknown).

4. Experimental Results

In this section, we construct a simple instance of a regional science and technology resources system, which we refer to as 'the entire system'. Suppose there are three subsystems in the entire system. To simplify the following calculation process, the optimization of the entire system and each subsystem is simplified as a single objective optimization. To make processing easier, the input-output relationship between the entire system and each subsystem is defined as a complex function. Relevant data for the entire system are shown in **Table 1**. In the experiment, the subsystems S_1, S_2, and S_3 can be designated as a research and development organization of enterprises, educational institutions, and scientific institutions. For each subsystem, it is very difficult to describe the relationship between evaluation indicators and performance indices using mathematical functions. Thus, the simulation model is applied to characterize the relationship between evaluation indicators and performance indices of subsystems. To simplify the experiments, simulation models are replaced by mathematical functions.

Table 1. Relevant data for the entire system

	Input-Output Relationship	Range of Variable	Simulation Time (Second)
Performance Comprehensive Analysis Module	$F = \max\left\{\sum_{i=1}^{3} S_i \sin\left(\sqrt{\lvert S_i \rvert}\right)\right\}$	$0 \le S_i \le 100$	3
Subsystem 1	$S_1 = \sum_{i=1}^{5} \text{integer}(x_{1i})$	$0 \le x_{1i} \le 20$	5
Subsystem 2	$S_2 = \sum_{i=1}^{10} \left(x_{2i}^2 - A\cos(2 \times \pi \times x_{2i})\right)$	$A = 20$ $-1 \le x_{2i} \le 1$	10
Subsystem 3	$S_3 = \frac{1}{20} \sum_{i=1}^{20} \left(x_{3i}^4 - 16x_{3i}^2 + 5x_{3i}\right)$	$0 \le x_{3i} \le 3.5$	20

To test the correctness and efficiency of the proposed method, the modified genetic annealing algorithm (MGAA) [26], mixed algorithm based on the genetic algorithm and simplex method (MAGAS) [27], immunity genetic algorithm (IGA) [28], orthogonal genetic algorithm (OGA) [29], hybrid genetic algorithm (HGA) [30], and genetic algorithm with local search (GALS) [31] were applied to compare performance. These seven methods were executed in MATLAB and the experimental results were obtained using a person computer with an Intel 2.4 G CPU with 256 MB storage. For the optimization process, the design parameters of each method were essentially the same (see **Table 2**). The experiences on parameter selection can refer to [16]. To avoid randomness in the optimization process, the ultimate results are the average value of multiple optimizations (100 optimizations in this paper). We adopted the following two approaches to accomplish partial experiments: holistic optimization and layered optimization. The efficiency of layered optimization can be identified, and the efficiency of a mixed search method is to be proved.

Table 2. Parameter settings for the proposed method

Parameter	Parameter Meaning	Value
B	The number of sub-spaces of feasible spaces in population initialization	3
Q_1	The level number of independent variables in population initialization	5
G	Population size	50
Q_2	The level number of independent variables in crossover operation	5
F	The factor number of independent variables in crossover operation	3
σ	Design parameter in mutation operation	0.01
SI	Unimproved subsequent iterations of global optimal solution	50
MI	Maximum iterations	500

The experimental results of system optimization with the adoption of seven methods and two channels are displayed in **Table 3**. We compare the efficiency of various methods using the objective function and computational time.

Table 3. Experimental results of the entire system with seven methods and two channels

Items	Methods	MGAA	MAGAS	IGA	OGA	HGA	GALS	Our Method
Objective Function	Holistic	131.86	180.71	183.19	184.73	189.84	186.27	207.66
	Layered	179.36	182.65	186.75	193.26	197.15	195.24	239.81
Simulation Time (hour)	Holistic	886.51	99.86	98.14	130.69	95.12	96.17	53.17
	Layered	270.39	55.18	71.39	85.67	73.19	78.62	9.19

First, the performance of the seven methods is compared from the point of view of the objective function. When the layered optimization strategy was applied to solve the problem, the objective function of the proposed method was best, whereas there was little difference between the objective functions of the other six methods. When the holistic optimization strategy was applied to solve the problem, the objective function of the proposed method was best and the objective function of the MGAA was worst, whereas there was little difference between the objective functions of the other five methods.

Second, the performance of the seven methods is compared from the point of view of computational time. When the layered optimization strategy was applied to solve the problem, the computational time of the proposed method was smallest, whereas the computational time of the MGAA was largest. When the holistic optimization strategy was applied to solve the problem, the computational time of the proposed method was smallest, whereas the computational time of the MGAA was largest.

From the experimental results, the following conclusions can be summarized. Regardless of which method we adopted, the efficiency of layered optimization was higher than holistic optimization. These results suggest that the layered optimization strategy is better than the holistic optimization strategy. To solve other complex optimization problems, the layered optimization strategy is a very worthwhile solution. Whether layer optimization or holistic optimization, the efficiency of the method in this paper was higher than the other methods. Therefore, the application of this method to solve the entire system optimization is feasible, correct, and effective.

5. Conclusion

The contribution of this paper can be summarized as follows: The regional science and technology resource allocation optimization was modeled as a double-layer optimization model. Additionally, a mixed search method was proposed based on the orthogonal genetic algorithm and sensitivity analysis. Experimental results suggest that the proposed method is feasible, correct, and effective.

Further research should consider how to address random factors in the system simulation process, how to further excavate and apply related knowledge in the optimization process, and how to improve optimization efficiency.

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