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Research Article

A Village Reconstruction Model Using Particle Swarm Optimization Algorithm

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In bygone days, the way to deal with traditional villages in developing new cities in China was often to overturn them and replace the original environment with the built-up urban environment, causing constructive destruction to the traditions and cultures. According to the new village transformation requirements, the planning and construction of villages must be shaped with their own cultural and humanistic characteristics of the habitat requirements. It does not favor demolishing large constructions by implementing a different environment. A traditional village is an essential spatial framework to retain the "mark" of the local characteristics of the new city. It can be an essential element in shaping the individual characteristics of the village by realizing the diversity of spatial forms and regional cultural connotations of the new village. Therefore, this paper proposes a new village transformation model based on traditional villages' social, economic, and spatial patterns, combined with a new particle swarm optimization (PSO) algorithm named multi-objective particle swarm optimization (MOPSO). The model transforms the village based on the required optimum resource allocation with the global solution. The experiment shows that the proposed model suits village renovation and modernization. The work is a step toward the advancements and betterment of rural development.

1. Introduction

Villages depend on the physical space formed by certain natural boundaries as the foundation of production and life. At the same time, they use this physical space as a link to form production and social relations [1]. Therefore, from the viewpoint of properties, production, and life, villages are not only the physical space but also have economic properties reflecting production relations and social properties reflecting social relations and cultural awareness of the village.

The present approach to modern rural transformation differs from that used for many years. First and foremost, the village must be combined. However, the author disagrees with the results of some village construction plans that have been prepared today. These villages have been planned as new villages in the hope of concentrating the formerly scattered rural settlements together and saving land. Theoretically, by adjusting the standards and layout of residential land, the villages save residential land and improve the living environment [2]. However, in practice, due to the heavy concept of "roots" in our traditional culture, the "local sentiment, the concept of poor order pattern," is particularly prominent in rural areas. However, this phenomenon is especially prominent in rural areas with new plans. The villagers cannot be forced to move to the new settlement; as a result, some residents have gone, while others are still in the same place. It increases the living area instead of decreasing it. Therefore, the author believes that the village planning should avoid big demolition and construction. Even new villages should be reduced as much as possible and can be replaced by the concept of "village renewal" [3]. Village rejuvenation refers to the preservation of local culture and tradition, as well as local features, varied enterprises, and the "village look," with an emphasis on environmental management planning in the village. Respect for the regional culture of the village, and the texture of the

form, in the original village is based on a reasonable and appropriate transformation.

This paper establishes and solves an optimal resource allocation model for village transformation based on a particle swarm optimization (PSO) algorithm to obtain the optimal resource allocation plan under different conditions. The main contents include the following:

(1) Forming a comprehensive evaluation function with social, economic, and ecological benefits as the objectives, establishing an optimal apportionment model based on the particle swarm optimization algorithm, and determining the parameter coefficients related to the optimal resource allocation model by combining the actual local transformation situation.

(2) Because of the limitations of the single-particle swarm optimization algorithm, the idea of the multi-objective particle swarm optimization (MOPSO) algorithm is proposed. It effectively overcame the shortcomings of the single-particle swarm optimization algorithm verified by simulation experiments and applied to the village transformation resource optimization allocation model.

(3) The MOPSO is used to solve the village resource optimization-based allocation model. The results show that the model is well adapted to solve the village transformation-based resource allocation problems, which is more reasonable and scientific, closer to the actual situation, and has good development prospects.

The paper consists of several sections, among which the contribution is distributed. The introduction section is followed by the related work in Section 2 having the existing research by ancestors. In Section 3, the methodology and experiment area elaborate on the proposed MOPSO and its mathematical implementations. The experimental results in Section 4 prove the sustainability and efficiency of the proposed village renovation model. Finally, the conclusion is explained in Section 5.

2. Related Work

The village transformation and rural development is an interesting topic for the research as they have many parameters to cater to during the renovation process. Based on the requirements of the villages, the respective developments were made. However, each time, the whole environment was transformed into a new environment causing several different allocation and resource problems. This section discusses different pieces of literature presented by researchers in recent years related to the new village transformations and PSO algorithm.

2.1. Studies on New Town Construction. Since Howard developed the conception of the idyllic city toward the end of the nineteenth century, the practice and theory of new city development have flourished. Many scholars have studied new city construction trends, design techniques, and the interpretation of new city planning situations. A series of interpretations have been made for the new city construction cases in various countries [4]. The new city construction in Paris has been studied. They believed that the development goal of Paris's new city attaches great importance to the region's overall development. In the race to maintain the continuity of urban space with considerable importance to integrating the original urban development, the planned construction sites can be organically integrated with the original construction sites [5].

Comparing and summarizing the development and utilization cases of old settlements in Britain, France, and Hong Kong, Tai Po's new town construction combined with Hong Kong and Fuzhou's new town planning cases, the authors in [6] proposed the design strategy of integrating the new town and old settlement development. It is believed that new town development models can be divided into government-market collaboration, market-led, and government-led [7].

2.2. Studies on Village Change. The first two are the descriptions of the formation stage of villages. In contrast, the first two are the description of the formation stage of the village, while the aspect of "change" is reflected in the comparison of the two tenses of "present" and "past." There has always been a focus on the morphology of the settlement from the perspective of the spatial grouping of the community in the village [8]. The change in the community is from the perspective of the community spatial clusters in the village.

Authors in [9] explored the design strategy of combining old age-appropriateness with the village by taking the ancient village of Hegou as the research topic. The author combines the theories of ancient village conservation models at home and abroad. The feasibility analysis of the village's location, environment, and adaptability is carried out in conjunction with the village's present development model. Based on the existing conservation model, a more reasonable model of recreational aging is proposed, and the concept is used for simulation design. Realize the protection and reuse of ancient villages to optimize the existing industrial chain for the national ancient village protection model [10].

In studying rural settlements in semi-urbanized areas, factors such as radiation and diffusion of large cities, industrial out-migration from urban areas, population suburbanization, and new town construction as external factors influencing the spatial development of rural settlements have been considered. In contrast, agricultural industrialization, rural nonagriculturalization, rural tourism, and new rural construction are internal factors promoting the spatial evolution of rural settlements [11]. This study investigated the degree of rural-urban integation along with the village land-use patterns.On the other hand, the study in [12] considered political, social, economical, and physical geographic factors to study the evolution of urbanization in Pearl River Delta's urban fringe areas and proposed the planning countermeasures.

Taking the Hui village in Dongying Town, Daming County, as the research object, the current situation and problems of Hui architectural style in Daming County through field research and literature review have been sorted out [13]. Combined with relevant examples, the principles of Hui architectural renovation were summarized. A comprehensive comparative analysis of the macro-level of entrance space, street space, landscape space, and architectural space layout has been made. The three meso-levels of material, color, and decoration were compiled. After the study, the architectural style of the Hui village in Daming County will be transformed into a versatile Hui characteristic style under the premise of unity and harmony [14].

It has been argued that the construction of villagers' participation mechanism in the transformation of old villages should be strengthened with the characteristics of localized resources [15]. Various blunders and hazards of government decisions in promoting planning approval and urban village transformation due to disregarding the essential issue of land value-added benefit distribution have been encapsulated. They propose countermeasures to solve the incongruity of land value-added benefit distribution in urban village transformation from the perception of institutional construction. It has also been argued that urban village transformation should aim at the welfare of the low-income mobile population in terms of their living quality under the leadership of local governments [15].

A comparative study of the demolition and reconstruction type of a hunting village has been conducted. It involves the progressive type of Xilong village in Guangzhou regarding the implementation subject, financing, transformation process, and spatial texture, and the impact on villagers' foreign population [16].

2.3. Particle Swarm Optimization (PSO) Algorithm. The particle swarm optimization algorithm is a metaheuristic algorithm that simulates the foraging behavior of a flock of birds and is increasingly used in practical engineering. The improvement work to address the shortcomings of the particle swarm optimization algorithm, such as premature convergence and the tendency to fall into local optimum, can be divided into three directions.

2.4. Introducing or Optimizing Hyperparameters. The introduction of inertia weights and shrinkage factors in turn compared the performance of these two time-varying parameters [17]. The adaptive nonlinearly varying inertia weights in the PSO algorithm, which allowed the algorithm to be coarsely tuned in the initial iterations to quickly approach the optimal solution and gradually fine-tuned in subsequent iterations to more accurately approximate the optimal solution, have been used [18].

2.5. Improving the Topology and Search Strategy of the Particle Population. According to the fitness value, the particle population is divided into active and inert groups [19]. They used orthogonal diagonalization to replace the original particle update strategy, which greatly improved the accuracy and speed of the algorithm. New particles for guidance by the Taguchi method have been constructed, which avoided the conflict between the two historical experiences [20].

2.6. Fusion with Other Optimization Algorithms to Complement Each Other's Advantages. Harmonic search (HS) and PSO were fused into a new optimization algorithm and analyzed its convergence performance by using Markov model [19]. Similarly, gray wolf optimization (GWO) and PSO were combined to obtain a hybrid algorithm [21]. Experiments by K-means clustering optimization show that the algorithm has good optimization performance and strong generality.

In correspondence to this, the system proposed is the enhanced version of the PSO, and the objective is to do minor required renovations to the village compared to the whole transformation.

3. Proposed Methodology

Each particle in the particle swarm optimization algorithm remembers the optimal historical positions it has found so far and the optimal historical positions found by its peers in the population. Therefore, the particle swarm optimization algorithm is more purposeful in finding the optimal position and has a clearer direction. The algorithm's advantages, such as fewer parameters, rapid convergence blocks, and easy integration with other algorithms, make the particle swarm optimization algorithm suitable for multi-objective optimization. Since Moore and Chapman first tried to solve multi-objective problems using the optimization strategy, the optimized particle swarm optimization algorithm has been widely used in various fields [22]. Because of this, the PSO algorithm is chosen to solve the multi-constrained combinatorial optimization problem in the paper.

The section consists of optimal positions, types, details, and more. Along with this, the MOPSO algorithm-related mathematical calculations are also discussed. Moreover, the solution is selected for the Pareto optimal system with all relevant calculations.

3.1. Selection of Global and Local Optimal Positions. The PSO has optimal solutions: local and global. Both the solutions operate on the particles, but the local operates on specific values of the particles, whereas the global operates on both. The preferred solution is based on the requirements of the system. A global optimum solution can be shifted to a local one, but vice versa is impossible. The following selections are explained as follows.

3.1.1. Selection of Individual Optimum (Pbest). In the multi-objective particle swarm optimization algorithm, the update strategy of Pbest is as follows:

(1) If the current particle can dominate the individual historical optimum Pbest in the Pareto dominance

relationship, then the current particle is used to replace Pbest.

(2) If the individual historical optimum Pbest dominates the current particle, then the current particle is not updated.

(3) If the target space values of both the current particle and the historical optimal solution Pbest are equal, the current particle is used to update the historical optimal Pbest.

(4) If there is no domination relationship between them, one of the particles is randomly selected as the updated individual optimal.

3.1.2. Global Optimum (Gbest). The global optimum particle Gbest leads the particles to the global optimum in the iterative process, optimizing the population Pareto domination surface. Therefore, the selection of Gbest directly determines the optimization result. Given this, the paper proposes to build an external archive set strategy to store the global optimal solution Pareto dominance surfaces' convergence and variety.

In the paper, the Gbest method is chosen by computing the similarity distance SD in the decision space for each particle in each iteration. One will select the local optimum solution whenever the specific particles are needed to be addressed. The external archive is provided in[23]

$$d(x_i, y_i) = \sqrt{\sum_{k=1}^{N} \left(x_{i,k} - y_{j,k}\right)^2}, \tag{1}$$

$$SD_i = \left(d(x_i, y_1), d(x_i, y_2), \ldots, d(x_i, y_H)\right), \tag{2}$$

where x_i denotes the particle in the population, y_i denotes the ($j = 1, 2, \ldots, H$) nondominated solutions in the external archive, N is the dimension of the particle, and H is the number of nondominated solutions in the external archive. This similar distance can indicate the actual distance between the population and the external archive set of ideal global particles. Then, the ASD between the particle and the external archive collection is calculated by using [23]

$$\mathrm{ASD}_i = \frac{\sum_{j=1}^{H} SD_{i,j}}{H}. \tag{3}$$

Distance between particle and external archive set ASD_i can be calculated by equation (3). After calculating the average similarity distance of all particles, the similarity distance matrix SD_i with multiple columns is derived. Using the comparison method, the particles smaller than the average similarity distance ASD_i are selected, and the external archive collection and the matching nondominated solutions are chosen.

3.2. Update Strategy of MOPSO Algorithm. The multi-objective particle swarm optimization (MOPSO) algorithm deals with multi-objective optimization problems, and its optimization result is a set of Pareto noninferior solution sets. The MOPSO algorithm is fast, easy to handle and implement, and suitable for transformation and allocation-based applications. The standard MOPSO algorithm has disadvantages such as easy local prematureness, slow convergence of particles, and poor diversity in finding the optimal solution [24]. To solve these shortcomings, the paper makes corresponding improvements to it. It applies the improved multi-objective particle swarm optimization algorithm to the research problem of optimizing the location of micro-fire stations at construction sites of giant projects.

The Pareto noninferior solutions found during the iterative process are stored in the introduced external archive set. A linear decreasing inertia weighting strategy is chosen to adjust the inertia weights' values during the particles' iterative process. This inertia weighting strategy allows the population to converge quickly in the early iterations and find the optimum over a larger range later. At the same time, the globally optimal solutions of particles are randomly selected from the Pareto noninferior solutions in the external archive, which can play a better role in population bootstrapping.

The global particle swarm optimization (GPSO) algorithm can be described in mathematical language in a D-dimensional space; the particle swarm contains M particles. Each particle represents an alternative solution to the optimization problem, and the ith particle update at the kth iteration step is given by

$$\begin{aligned} v_i^{k+1} &= K\left[\omega v_i^k + c_1 r_1 \cdot \left(p_i^k - x_i^k\right) + c_2 r_2 \cdot \left(g^k - x_i^k\right)\right], \\ x_i^{k+1} &= x_i^k + v_i^k, \end{aligned} \tag{4}$$

where $v_i^k = (v_{i1}, v_{i2}, \ldots, v_{i\,D})$ is the particle velocity, $x_i^k = (x_{i1}, x_{i2}, \ldots, x_{i\,D})$ is the particle coordinate, p_i^k represents the particle history optimal solution, g^k represents the particle swarm history optimal solution, $\cdot$ denotes Hadamard product, c_1, c_2 denote acceleration factors, which generally take the value of 2, r_1, r_2 are D-dimensional vectors of random numbers among 0 and 1, ω denotes the inertia weight factor, K is the compression factor, and ω and K are generally set as linear or nonlinear functions of k, as shown in equation (2).

$$\begin{aligned} \omega &= \omega_{\max} - \left(\omega_{\max} - \omega_{\min}\right)\frac{K^2}{N^2}, \\ K &= \frac{1}{4}\left[\cos\left(\frac{\pi k}{N}\right) + 0.25\right]. \end{aligned} \tag{5}$$

The range of variation of ω is often taken as $\omega_{\max} = 0.9$ and $\omega_{\min} = 0.4$. N is the maximum total number of iterations.

Representing the particle swarm information in matrix form can be written as

$$\begin{aligned} X^k &= \left[\left(x_1^k\right)^T, \left(x_2^k\right)^T, \ldots, \left(x_M^k\right)^T\right], \\ V^k &= \left[\left(v_1^k\right)^T, \left(v_2^k\right)^T, \ldots, \left(v_M^k\right)^T\right], \\ P^k &= \left[\left(p_1^k\right)^T, \left(p_2^k\right)^T, \ldots, \left(p_M^k\right)^T\right], \end{aligned} \tag{6}$$

where X^k, V^k, P^k ($k = 0, 1, 2, \ldots, N$) is the matrix of $M \times D$.

As shown in Figure 1, it is the multi-objective particle swarm optimization algorithm's basic steps.

The advantage of the search strategy of equation (1) is that it enables the particles to be quickly concentrated at the minima, but its disadvantage is also obvious. Because of the lack of diversity in the data of this search strategy, once the algorithm is trapped in the minima, it is difficult to jump out of the local optimum, and it is often more difficult to search for the global optimum solution in the end.

3.3. Challenges in the MOPSO Algorithm. The following issues need to be resolved when using the multi-objective particle swarm optimization algorithm for micro-fire station siting model for the construction site of the giant project.

(1) Parameter Setting:

For different optimization problems, how to choose the appropriate parameters to achieve the optimal effect is a problem to which MOPSO pays attention [25]. An appropriate parameter setting can enable the algorithm to arrive at an accurate and effective Pareto optimal solution. The number of particles impacts the algorithm's search range, making obtaining the global best solution much easier.

(2) Dynamic Adjustment of Speed:

When the algorithm lacks the dynamic adjustment of the velocity, it is easy to fall into the local optimum, resulting in low convergence accuracy and difficulty in converging. The appropriate setting of the maximum velocity $V_{\max}$ of the particle is the key to whether the particle can find the optimal region. If $V_{\max}$ is set too large, the particle will easily fly away from the optimal region. If $V_{\max}$ is too tiny, the particle may not be able to detect the region outside the optimal local region adequately.

3.4. Selecting the Best Solution from the Pareto Optimal Solution. In accordance with the need to consider quantitative factors and qualitative factors in the decision-making of the village transformation problem of the giant project, this paper selects the TOPSIS method based on fuzzy triangular numbers to assess the comprehensive factors of each site selection solution and then determines the final decision solution for the location of the micro-fire station at the construction site of the massive project [26]. The calculation steps are as follows.

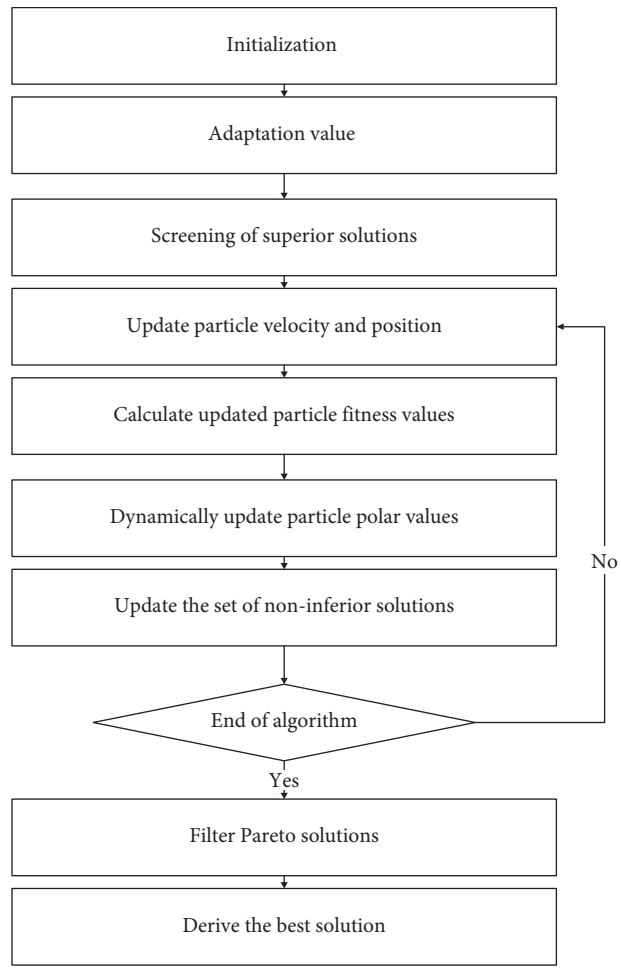

Figure 1: Diagram of multi-objective particle swarm optimization algorithm.

Step 1: Construct the affiliation function of fuzzy information. When the experts describe the index weights and index values, the paper uses fuzzy semantic words: very important, important, average, unimportant, very unimportant and very good, good, average, poor, and very poor. They are transformed into triangular fuzzy numbers as (0.7, 1, 1), (0.5, 0.75, 1), (0.3, 0.5, 0.7), (0, 0.25, 0.5), and (0, 0, 0.3).

Step 2: Construct the decision matrix. Let the set of experts participating in the solution decision be $D = \{Dk, k \in 0\}$, $O = \{1, 2, \ldots, g\}$, Dk is the kth expert, and g is the number of experts; the set of solutions is $E = \{Ei, i \in$ m$\}$, $M = \{1, 2, \ldots, m\}$, Ei is the ith solution, and m is the solutions number; $F = \{Fj\ j \in N\}$ is the jth indicator, and n is the number of indicators; then, w_{jk} denotes the fuzzy evaluation value of the kth expert on the weight of

indicator j, $w_{jk} = (w_{jk1}, w_{jk2}, w_{jk3})$ is the triangular fuzzy number, x_{ijk} denotes the fuzzy evaluation value of the kth expert on indicator j of the ith solution, $x_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk})$ is the triangular fuzzy number. The fuzzy expert group decision matrix D and the fuzzy expert group weight matrix W are, respectively,

$$D = \begin{bmatrix} x_{111} & x_{112} & \dots & x_{11g} \\ x_{211} & x_{212} & \dots & x_{21g} \\ x_{m11} & x_{m12} & \dots & x_{m1g} \\ x_{2n1} & x_{2n2} & \dots & x_{2ng} \\ x_{mn1} & x_{mn2} & \dots & x_{mng} \end{bmatrix}, \quad D = \begin{bmatrix} \omega_{11} & \omega_{12} & \dots & \omega_{1g} \\ \omega_{21} & \omega_{22} & \dots & \omega_{2g} \\ \dots & \dots & \dots & \dots \\ \omega_{n1} & \omega_{n2} & \dots & \omega_{ng} \end{bmatrix}. \tag{7}$$

The fuzzy set decision matrix $\widetilde{D}$ and the fuzzy weight vector $\widetilde{\omega}$ can be obtained by calculating the matrix D and the matrix W. The formula is

$$\begin{aligned} \widetilde{D} &= \left[x_{ij}\right]_{m*n} = \left[\left(a_{ij}, b_{ij}, c_{ij}\right)\right]_{m*n}, \\ \widetilde{\omega} &= \left[\omega_{ij}\right]_{m*n} = \left[\left(\omega_{j1}, \omega_{j2}, \omega_{j3}\right)\right]_{m*n}. \end{aligned} \tag{8}$$

Step 3: Normalize the decision matrix. For multi-attribute decision problems, the objectives are not commensurable; i.e., each element in the decision matrix has a different magnitude. Therefore, when making decisions, the decision matrix should be standardized to reduce the impact of the scale on the outcome.

Step 4: Calculate the standardized fuzzy weighted decision matrix. The standardized fuzzy weighted decision matrix is computed as

$$\widetilde{D}_{\omega} = \left[z_{ij}\right]_{m*n} = \left[\left(\widetilde{a}_{j1}, \widetilde{b}_{j2}, \widetilde{c}_{j3}\right)\right]_{m*n}, \tag{9}$$

where $z_{ij} = y_{ij} \times \omega_j$.

Step 5: Find the fuzzy optimal and inferiority vectors (corresponding to positive and negative ideal solutions). To combine the TOPSIS method with the fuzzy triangular numbers, the paper defines the positive and negative ideal solutions, respectively, as

$$\begin{aligned} E^{+} &= \left[x_j^{+}\right]_{1\times n} = \left[\left(a_{a,j}^{+}, a_{b,j}^{+}, a_{c,j}^{+}\right)\right]_{1\times n}, \\ E^{-} &= \left[x_j^{-}\right]_{1\times n} = \left[\left(a_{a,j}^{-}, a_{b,j}^{-}, a_{c,j}^{-}\right)\right]_{1\times n}. \end{aligned} \tag{10}$$

Step 6: Calculate and obtain the ideal degree. Calculate the ideal degree C_i for any evaluation object i. The formula is $C_i = E^{-}/E^{-} + E^{+} Ci = [0,1]$. If C_i is closer to 1, the object i is closer to the optimal standard, the more active; if C_i is closer to 0, the object i is closer to the worst standard, the less active.

Step 7: Evaluation ranking. The evaluation objects are ranked according to the size of C_i value, and the optimal object or even the overall operation situation is selected.

4. Experiment and Analysis

The section presents an analysis of MOPSO and its parameters implemented through the following mathematical equations. All the experiments examine the village model for the optimal allocations and can be implemented practically.

4.1. Analysis of the Results of the Model for Optimal Allocation of Village Resources. According to the distribution of village resources, the multi-objective particle swarm optimization algorithm is used to solve the above resource optimization, allocation model. The results of resource optimization allocation of village resources in different plans and scenarios are obtained. Table 1 consists of all the resultant demand points and their assessment levels.

Table 1 shows the assessment level of the demand points within the village during its renovations.

4.2. Simulation Verification under Test Function. Simulation verification using the multi-objective particle swarm optimization technique: The objectives of the simulation mainly include (a) to compare the performance of the adaptive algorithm with that of the nonadaptive algorithm under different metrics and (b) to compare the average performance and robustness of the adaptive and nonadaptive algorithms concerning the key parameters. The parameter settings and time cost of the optimization algorithm are depicted in Table 1. The parameters are set as follows: PSO parameters: number of population particles $N = 30$, maximum velocity of particles $v_{\max} = 2$, learning factor $c_1 = c_2 = 1$, and maximum number of iterations $t_{\max} = 150$.

(a) Preference Control Parameters of the Nonadaptive Algorithm: preference reference point move step = 0.01, initial preference reference point position (0, 0).

(b) Preference Control Parameters for the Adaptive Algorithm: adaptive step coefficient $k_{\text{adaptive}} = 1/2$, elasticity coefficient $k_{\text{damoce}} = 0.37$, initial preference reference point location (0, 0).

4.3. Cost of Spending Comparison. In this paper, we use simulation software to conduct a cost comparison study of the village transformation model based on the particle swarm optimization algorithm; the proposed model is selected from the basic PSO and the improved MOPSO model; the specific results are shown in Table 2.

From the results obtained, it is clear that the cost of the retrofit solution calculated with the improved algorithm is almost half.

Table 1: Village site-level assessment form.

Serial number	Demand point	Assessment level
1	Settlement house	5
2	Park 1	2
3	Park 2	2
4	Electricity distribution room	4
5	Public toilet	3
6	Public activity square	4
7	Sewage treatment plant	2
8	Parking lot	4
9	Workshops	3
10	Ancestral hall	3

Table 2: Optimization results of algorithms.

Algorithm	Residence	Optimal location	Investment (thousand)
PSO	1	(13.491, 12.334)	1.28
	2	(16.320, 10,554)	
MOPSO	1	(9.669, 17.539)	0.72
	2	(17.445, 10.432)	

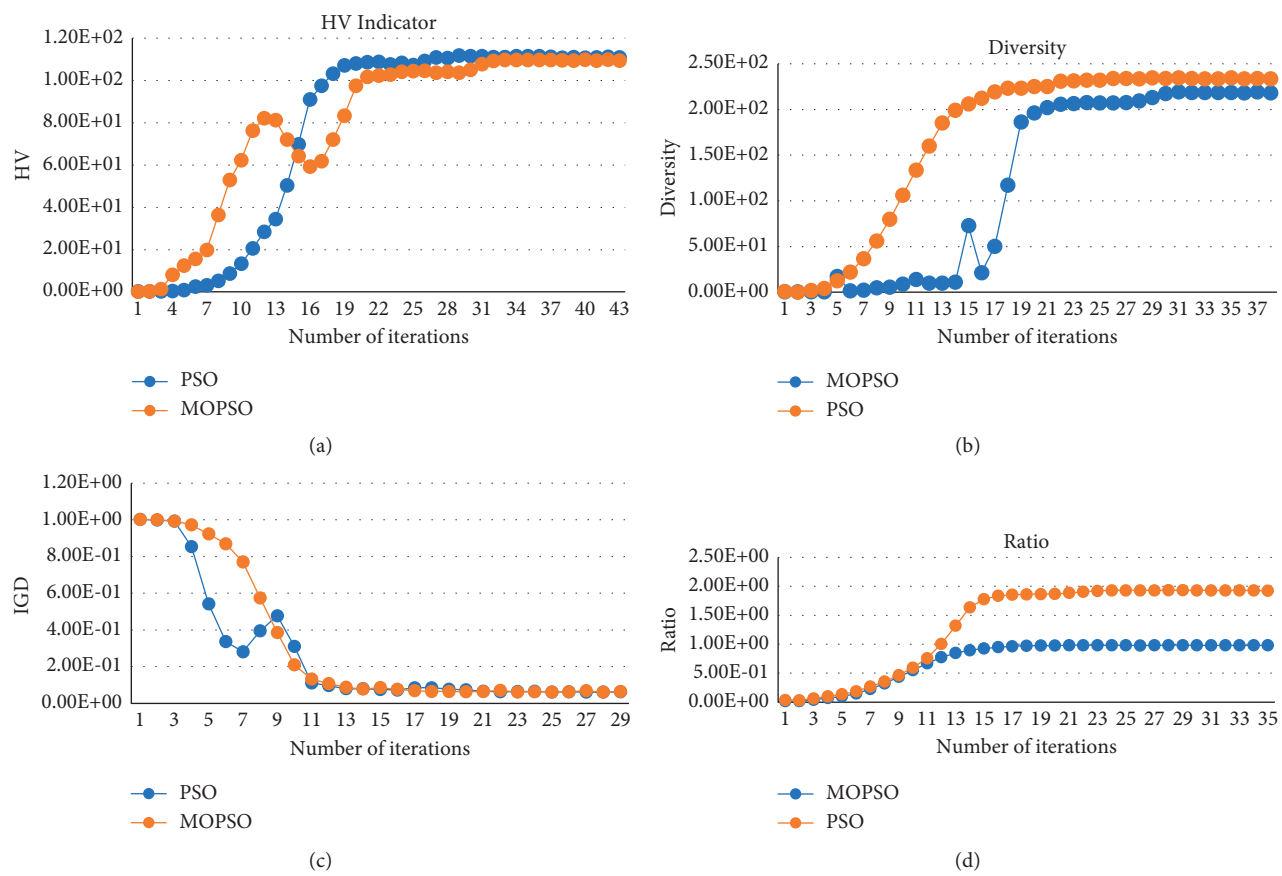

Figure 2: Comparison of adaptive and nonadaptive algorithms under the ZDT1 test function. (a) HV indicator. (b) Diversity. (c) IGD. (d) Ratio.

4.4. Model Adaptability Analysis. The Monte Carlo count is set to 500, the radius of the preference area = 0.02, and the ZDT1 test function is 80 degrees; the adopted metrics are HV under preference, diversity under preference, IGD under preference, and ratio, where the HV reference point is chosen at (11, 11). As shown in Figure 2, it is the simulation results.

The graph shows several different variations for the MOPSO and PSO algorithms corresponding to several parameters. HV and diversity increase with the increase in

the number of iterations; the ratio first increases and then becomes constant on different values for both PSO and MOPSO. However, the IGD decreases with the increase in the number of iterations. From all the graphs, it can be observed that the PSO has higher values than the MOPSO. The reason is that the MOPSO algorithm is derived from the PSO and lacks some features; otherwise, it has the same trends as the PSO.

5. Conclusion

At the moment, the concepts of modern rural transformation diverge. According to this document, village planning should prevent large-scale destruction and building, and even new settlements should be kept to a minimum. The concept of "village renewal" can be used instead. Village renewal refers to the planning that combines local characteristics with various business operations based on preserving local cultural traditions, combining with "village appearance," and paying attention to village environmental management. This paper establishes the optimal resource allocation model for village renewal and solves it based on a particle optimization algorithm to get the optimal resource allocation scheme under different conditions. We construct a comprehensive evaluation function targeting social, economic, and ecological benefits, establish the optimal allocation model based on the particle swarm optimization algorithm, and determine the parameter coefficients associated with the optimal resource allocation model by combining the actual situation of local renovation. We propose the idea of introducing a multi-objective particle swarm optimization algorithm in the basic particle swarm optimization algorithm to address the limitations of the single-particle swarm optimization algorithm and multi-objective particle swarm optimization algorithm, which effectively overcomes the defects of the single-particle swarm optimization algorithm and is validated by simulation experiments and applied to the optimal resource allocation model for village transformation. The experimental results show that the MOPSO algorithm is a valid and effective solution for the village allocation optimization. The paper is the base for the MOPSO-based village renovations and developments in the near future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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