Optimizing The Allocation Of Rural Cultural Resources Using Genetic Algorithms

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Efficient distribution of rural cultural resources is essential for sustainable development under China's rural revitalization strategy. This study presents a scalarized multi-objective genetic algorithm optimizing utilization, tourism appeal, costs, and sustainability under constraints. Tested on 30 simulated resources, it outperforms heuristics, improving utilization by 14.47%, reducing costs by 19.72%, and increasing sustainability scores by 1.18 points.

Keywords: Rural cultural resource allocation, Genetic algorithm optimization, Sustainable rural tourism, Multi-objective decision support, China rural revitalization

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1. Introduction

Rural cultural resources preserve identity and promote sustainability [1]. Effective rural cultural resources boost connections, well-being, development. Optimized site allocations guide sustainable rural heritage development [2]. Effective rural cultural resources boost connections, well-being, development [3]. Rural cultural investments achieve effectiveness through practical improvements [4] Study combines culture with genetic algorithms optimizing resources.

2. Materials and methods

Wang et al. [5] Ningxia water distribution optimization using PSO-SA. These studies emphasize cultural value, participation, sustainability; quantitative methods limited. Natesha and Guddeti [6] Optimizes IoT placement reducing cost, time, energy. Cloud optimization handles constraints; rural uses sustainability optimization. Fig. 1 shows genetic algorithm optimizing rural cultural resource distribution for sustainability. The proposed framework sequentially clean data, define variables, encode chromosomes, optimize GA. Genetic algorithms allocate rural cultural resources with encoding (where each gene is represented as a continuous numerical value rather than a binary value) to create an exact representation of actual investment and allocation decision-making processes. Real-valued chromosome encoding represents proportional investments using continuous ratio variables.

Algorithm optimizes rural resources selection mutation evaluation (Fig. 2) The initial population is formed by randomly creating feasible chromosomes. Chromosomes initialized by random allocation ratios within bounds; crossover mutation explore space.

$$P^0 = \left\{X_1^0, X_2^0, \ldots, X_N^0\right\} \tag{1}$$

In this Eq. (1), P^0 represents initial population, X_k^0 denotes chromosomes. The chromosome represents allocation variables associated with rural cultural resources, where gene values indicate allocation intensity, ranking, and resource prioritization. Parent chromosomes are selected using tournament selection, subset sampled randomly; fittest chosen, promoting quality and diversity.

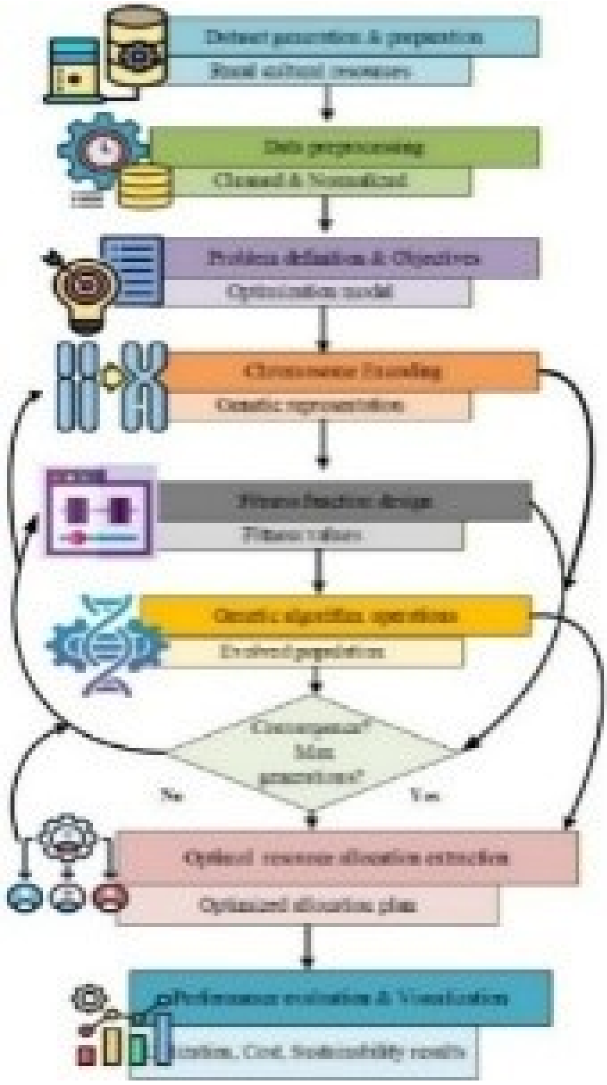

Fig. 1. Proposed genetic algorithm–based rural cultural resource allocation framework

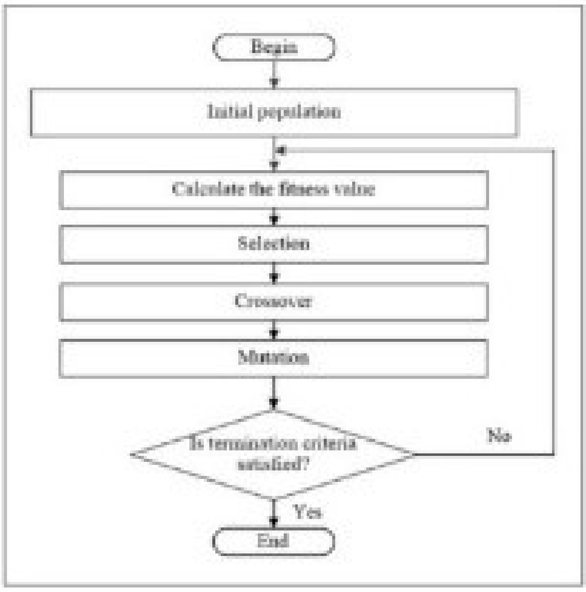

Fig. 2. Overall workflow of the proposed genetic algorithm

Gaussian perturbations are applied to gene values during mutation, magnitude of variation determined by underlying distribution parameters guiding changes. Gaussian mutation is applied to introduce small, normally distributed perturbations support smooth exploration and stable solution refinement. The system uses this method to stop early solution convergence while investigating alternative potential solutions. Constraint preservation is incorporated within crossover and mutation operations to maintain adherence to predefined budget limits. Adjusted offspring normalized proportionally, maintaining feasibility within allocation bounds.

A multi-objective fitness function (a mathematical measure used to evaluate the quality of each allocation solution) is designed to fitness function evaluates quality optimizing resource cost sustainability. The policy-oriented fitness evaluation mechanism incorporates sustainability by evaluating resource allocations through a combination of environmental, social, and economic factors. Includes sustainability score using cultural importance, tourism attractiveness metrics. The strategy evaluates how capital optimizes rural cultural facility operations.

$$U = \frac{1}{R} \sum_{r=1}^{R} u_r \tag{2}$$

Eq. (2)) represents average utilization improvement across cultural resources (R). The utilization improvement metric measures the change in usage of each rural cultural facility following budget allocation. Percentage increase in utilization after optimization measuring operational performance.

$$S = \frac{1}{R} \sum_{r=1}^{R} s_r \cdot g_r \tag{3}$$

Eq. (3) evaluates sustainability using resource scores, allocation ratio, and costs. The optimization objective incorporates utilization efficiency, tourism attractiveness, maintenance expenditure, Integration balances priorities improving usage, tourism, costs, sustainability outcomes overall. The fitness function incorporates weight parameters to balance resource utilization, tourism attractiveness, The genetic algorithm ends with its best. The genetic algorithm ends with its best solution found after analyzing all available solutions in the final population. Selected chromosome achieves maximum performance increases usage appeal decreasing expenses.

Algorithm 1. Genetic Algorithm for Rural Cultural Resource Allocation

Require:
Cleaned and normalized rural cultural resource dataset
Population size N
Maximum generations G
Crossover probability P_c
Mutation probability P_m
Fitness function $F(\cdot)$
Ensure: Optimal resource allocation chromosome X^*
1: Initialize population and evaluate fitness of each chromosome using $F(\cdot)$
2: Select parents from the current population
3: Apply crossover with probability P_c
4: Apply mutation with probability P_m
5: Repair offspring to satisfy resource and cultural constraints
6: Evaluate fitness of the offspring
7: Apply elitism to form the next generation
8: Repeat steps 2–7 for $g = 1$ to G
9: **return** the best chromosome X^*

A desktop with Intel Core i5-12400, 8GB RAM, Python 3.11.9, and 3-5s computation time. The study evaluates a genetic algorithm framework using synthetic rural data. Township cultural facilities: temples, heritage sites, importance-tourism-cost-utilization-sustainability. A simulated dataset of 30-resource dataset heritage-significance, cultural-importance, tourism-attractiveness uniform; costs normal; utilization linear; sustainability composite. Researchers simulated village resources; study analyzes 30 resources, 20-40 China. Numerical attributes of the dataset were cleaned and standardized before genetic algorithm optimization. Missing values replaced; infeasible corrected; variables normalized for fairness. Cultural-importance heritage; tourist- attractiveness visitors; utilization usage; cost expenses; capacity-limits; sustainability. The synthetic dataset follows domain-informed statistical assumptions to represent variability in rural cultural resource characteristics. Cultural, tourism uniform; maintenance normal; capacity bounded uniform distributions.

Tourism attractiveness quantifies the appeal of each cultural facility to visitors, Higher tourism attractiveness increases visitors, boosts economy, enhances cultural participation. Similar to cultural importance, this attribute was generated Eq. (4)

$$TA_i \sim U(1, 10) \tag{4}$$

where TA_i represents the tourism appeal of the i^{th} resource. Cultural sustainability influences tourist attraction, with random factors affecting outcomes. In this study, data preprocessing ensures the quality, consistency, and suitability of the simulated rural cultural resource dataset for genetic algorithm-based optimization. This step standardizes data; Eq. (5) clearly presents

$$x_r^{norm} = \frac{x_r - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

Here, x_r by scaling it between $[0, 1]$ for optimization. Genetic algorithm uses population100 generations200 tournament3 crossover0.8 mutation0.05 elitism5% encoding. Tournament selection size determines the selection pressure within the genetic algorithm. Larger tournaments favor exploitation; smaller maintain diversity; elitism preserves best solutions. Chromosomes represent genes; GA optimized weighted sum, tested 30 experiments stability

3. Results & discussion

Genetic algorithm improves resource allocation, sustainability, reduces costs, supports rural revitalization. An increase in the number of rural cultural resources results in an expansion of the search space, Higher complexity increases computation, but GA ensures stable convergence quality. Moderate cultural-resource use, high cost and sustainability differences. Maintenance cost reduction reflects allocation efficiency under constrained budget ensuring sustainable planning. Fig. 3 shows two clusters: $20-35\%$ and $60-80\%$ utilization scale. Fig. 4 shows fitness scores

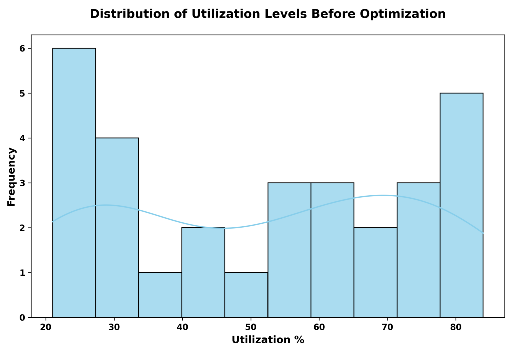

Fig. 3. Distribution of Current Utilization Levels Before Optimization

evolution across generations during optimization. The convergence behavior of the genetic algorithm is characterized by a gradual improvement in fitness values over successive generations, Stable convergence trend shows balanced exploration, exploitation, robust optimization performance. x

-axis shows generations, y -axis fitness; performance fluctuates during exploration, exploitation.

The proposed genetic algorithm optimizes utilization, cost, sustainability efficiently. Optimized increase utilization 1.78%-14.47%; Village C 14.47%, A 11.68%; GA 14.47% ± 1.82 robust

The Table 2 summarizes RMSE, MAE, utilization, cost reduction, and sustainability scores for Random, Proportional, and Proposed GA methods.

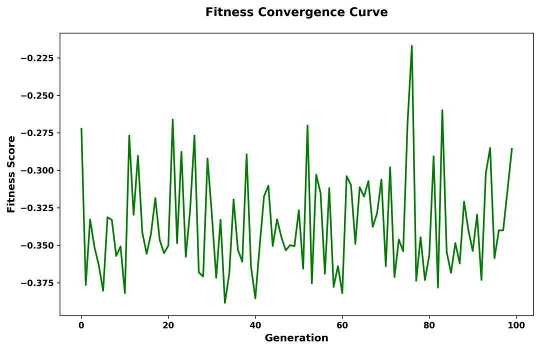

Fig. 4. Fitness convergence curve

Fig. 5 shows resource utilization before and after optimization, indicating improvement.

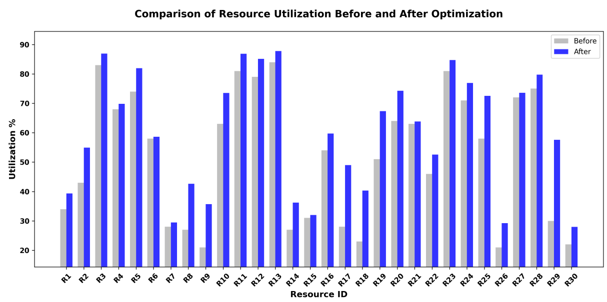

Fig. 5. Comparison of Resource Utilization Before and After Optimization

Optimization strategy reduced maintenance costs for most resources, Fig. 6.

Optimization resulted in cost savings, improving efficiency and resource management. Fig. 7 shows sustainability scores for R1-R30 post-optimization improvement.

Optimization boosted most resources' sustainability scores from 4-6 to 7-9, while high performers showed slight gains. Table 1 shows MOPSO [7] matches NSGA-II but requires more power. PSO [8] is fast but lacks diversity.

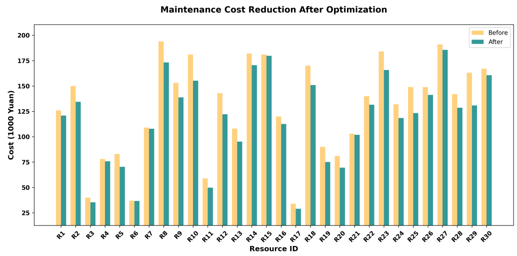

Fig. 6. Maintenance Cost Reduction After Optimization

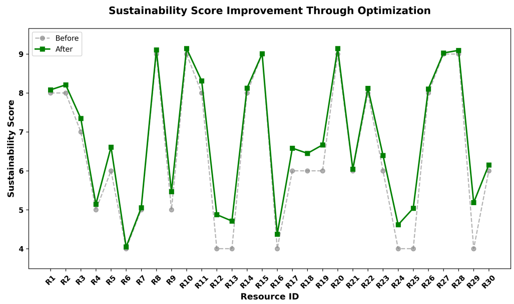

Fig. 7. Sustainability Score Improvement Through Optimization

4. Conclusion

Framework optimizes distribution, improving usage and reducing costs by 19.72%. Future research will incorporate administrative data, spatial datasets, and multi-objective algorithms like NSGA-II to optimize rural cultural resource allocation. Hybrid metaheuristics and stakeholder modeling improve adaptability and solution diversity.

5. Acknowledgement

6. Declarations

7. Data availability

The data used in this study were generated through simulation to reflect rural cultural resource allocation scenarios in China. The simulated dataset of 30 rural cultural resources is available from the corresponding author upon reasonable request. No publicly available datasets were used.

8. Conflicts of interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

9. Funding statement

This research received no external funding.

Table 1. Comparison of optimization algorithms

Algorithm	Type	Solution Quality	Computational Efficiency
MOPSO [7]	Swarm intelligence	Comparable to NSGA-II in convergence	Higher per-generation cost than NSGA-II in some cases
PSO [8]	Swarm intelligence	Fast early convergence but weaker diversity	High computational speed
Proposed scalarized GA	Single-objective GA via weighted multi-objective scalarization	High overall performance in utilization, cost reduction, and sustainability	Moderate runtime (3–5 s per run for 30 resources and 200 generations); scalable with $\mathcal{O}(N \cdot G \cdot M)$

Table 2. Comparative Performance Metrics of Allocation Methods

Method	RMSE ↓	MAE ↓	Utilization ↑	Cost Reduction ↑	Sustainability Score ↑
Random Allocation	0.182	0.145	4.12%	2.05%	0.12
Proportional Allocation	0.121	0.098	8.45%	7.36%	0.52
Proposed GA	0.065	0.051	14.47%	19.72%	1.18

10. Author contribution

Hui Ding solely conceived and designed the study, developed the optimization model, conducted data simulation and analysis, interpreted the results, and prepared the manuscript.

11. Ethical approval

This study does not involve human participants, animals, or personal data. Therefore, ethical approval was not required.

12. Consent to participate

Not applicable. The study does not involve human participants.

13. Consent to publication

The author consents to the publication of this manuscript.

14. Competing interests

The author declares that there are no competing interests.

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