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OPTIMIZING BLOCK-BY-BLOCK RELOCATION IN HISTORIC URBAN RENEWAL: A HYBRID SIMULATED ANNEALING-GENETIC ALGORITHM APPROACH

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Abstract: This study presents an innovative computational framework addressing the complex optimization challenges in historic urban renewal through block-by-block relocation strategies. This study develop a hybrid simulated annealing-genetic algorithm (SA-GA) that synergistically combines the global search capability of genetic algorithms with simulated annealing's local optima avoidance mechanism. The model incorporates three critical optimization objectives: (1) maximization of contiguous cleared blocks (demonstrating 28.3% improvement), (2) minimization of resident displacement (achieving 19.7% reduction), and (3) preservation of neighborhood spatial integrity. This study's comprehensive compensation scheme accounts for multiple architectural factors including housing orientation, unit area differentials, spatial configuration metrics, daylight access preservation, and structural renovation requirements. Computational experiments reveal the SA-GA hybrid's superior performance, showing 24.1% better solution quality and 17.3% faster convergence compared to conventional methods. The framework features: A cost-benefit analysis module identifying optimal ROI thresholds, Resident satisfaction metrics (85.2% acceptance rate in simulations)Implementation cost optimization(23.4% savings potential), Decision-support software implementation This research contributes both theoretically and practically by: Establishing the first application of SA-GA in urban building relocation, Developing quantifiable fairness assessment metrics, Providing actionable tools for large-scale renewal projects.
Keywords: Urban renewal; Building relocation optimization; Hybrid metaheuristics; Multi-objective decision making; Computational urban planning; SA-GA algorithm

1 INTRODUCTION

Urban renewal in historic districts has emerged as a critical challenge in global urbanization, balancing preservation of cultural heritage with modernization demands[1]. Traditional relocation strategies often face conflicts between resident satisfaction and developer profitability, necessitating innovative optimization frameworks[2]. Recent advances in computational intelligence, particularly hybrid algorithms, offer promising solutions for multi-objective urban planning[3]. Genetic algorithms (GA) have demonstrated efficacy in spatial optimization, as evidenced by Li et al. in their Beijing hutong renewal study[4]. Meanwhile, simulated annealing (SA) has been integrated with GA to overcome local optima in complex constraint environments, as shown in Chen et al.'s infrastructure planning model[5]. Cost-benefit analysis remains pivotal for evaluating urban renewal viability. Smith and Johnson established dynamic cost models incorporating temporal rent fluctuations, while Tanaka et al. quantified cultural value preservation in Japanese machiya districts[6-7]. However, existing studies inadequately address the "gain zero point" concept – the threshold where marginal renewal benefits diminish – identified as crucial by the EU Urban Agenda[8].

In China, rapid urbanization intensifies pressure on courtyard-style neighborhoods. Wang's survey of 1,000 Beijing residents revealed that 68% prioritize daylight access over financial compensation, aligning with global findings from Parisian Haussmannian renewal projects[9-10]. Comparative studies by González et al. Further highlight cultural-specific weighting of relocation factors across Mediterranean and Asian cities[11].

This study advances prior work through three innovations: (1) A novel SA-GA hybrid algorithm optimizing both spatial adjacency and cost constraints; (2) Quantitative integration of psychometric factors ($\alpha_{coefficient}$) into compensation models; (3) Dynamic gain zero point identification using time-discounted cash flow analysis. Our methodology builds upon but significantly extends the frameworks of Zhang et al. and European Urban Institute's renewal guidelines[12-13], while addressing limitations in Müller's static cost models of limited applicability, For the case of static fixed costs, without inputting special assumptions, the number of companies is difficult to determine, and the model is difficult to effectively handle this situation. For the case of static cost - reduction, the conclusion of the model may be invalid in the context of monopoly pricing. Because when a domestic enterprise forms a monopoly, its price path is complex, and the model is difficult to effectively restrict and predict. At this time, protection according to the model conclusion may be unreasonable[14].

2 MODEL FORMULATION FOR BIOCK RELOCATION OPTIMIZATION

This section presents a multi-objective optimization framework to address the block-by-block relocation problem in historic urban renewal. The model integrates spatial planning principles with economic viability analysis to balance three critical objectives: maximizing contiguous vacant blocks, minimizing resident displacement, and controlling developer costs.

2.1 Objective Functions

The optimization model simultaneously pursues three primary goals through weighted aggregation:

2.1.1 Maximizing contiguous vacant area

$$\text{Maximize } Z1 = \sum_k y_k \text{Area}_k + 0.5\Sigma_{(k,l)\in Adj} y_k y_l (\text{Area}_k + \text{Area}_l) \tag{1}$$

where y_k is Binary variable (1 if block k is vacated; 0 otherwise), Adj is Set of adjacent block pairs.
The coefficient 0.5 avoids double-counting adjacency relationships.

2.1.2 Minimizing relocated households

$$\text{Minimize } Z_2 = \Sigma_{i,j} x_{ij} \tag{2}$$

where x_{ij} is Binary variable (1 if household i relocates to block j; 0 otherwise).

2.1.3 Cost control

$$\text{Minimize } Z_3 = \Sigma_i (3 + C_{\text{repair, i}} + 3650\, \Delta 6_{\ i} r_i) \tag{3}$$

where $C_{\text{repair},i}$ is Renovation cost (≤200,000 CNY), ΔA_i is Area difference between new/old residences and r_i is Original rental value (8-15 CNY/m²/day).

2.2 Constraints

The model incorporates six categories of constraints to ensure practical feasibility:
Area Compensation

$$A_j \geq A_i \text{ and } A_j \leq 1.3 A_i \ \forall i,j\ (x_{ij} = 1) \tag{4}$$

Ensures relocated households receive ≥100% and ≤130% of original area.
Lighting Conditions

$$O_j \geq O_i \ \forall i,j\ (x_{ij} = 1) \tag{5}$$

Orientation scores: South/North=4, East=3, West=2.
Budget Limit

$$\Sigma_i (3 + C_{\text{repair,i}} + 3650\Delta 6_{\ i} r_i) \leq 26{,}000{,}000 \text{ CNY} \tag{6}$$

Single Relocation

$$\Sigma_j x_{ij} \leq 1 \ \forall i \tag{7}$$

Each household relocates at most once.
Single Occupancy

$$\Sigma_i x_{ij} \leq 1 \ \forall j \tag{8}$$

Each vacated block receives ≤1 household.
Satisfaction Threshold

$$S_i = w_1 \frac{A_{\text{new}}}{A_{\text{old}}} + w_2 \frac{O_{\text{new}}}{O_{\text{old}}} + w_3 \frac{C_{\text{repair,i}}}{20} + \alpha_i + \beta_{\text{facility,i}} \geq 0.7 \tag{9}$$

Validated through surveys (Cronbach's α=0.82).

2.3 Hybrid SA-GA Algorithm

To solve this NP-hard combinatorial optimization, we implement a hybrid simulated annealing-genetic algorithm (SA-GA) with enhanced global search capabilities:
In the genetic operations part of the hybrid SA - GA algorithm:
For encoding, chromosomes combine $x_{ij}$and $y_k$into binary strings, which digitizes the relevant variables in the problem, facilitating subsequent processing by the algorithm.
The selection operation adopts tournament selection with a size of 5. This method can preserve elite solutions. By selecting a certain number of individuals in the population for competition, individuals with higher fitness have a greater chance of entering the next generation, thus guiding the algorithm to search in the direction of better solutions.
The crossover operation uses two - point crossover with a crossover probability P_c=0.8That is two crossover points are randomly selected on the gene sequence of chromosomes, and the gene information of the corresponding segments is exchanged, increasing the diversity of the population and helping to explore the new solution space.

The mutation operation is bit - flip mutation with a mutation probability P_m=0.01 It randomly changes the values of some gene bits on chromosomes with a small probability, preventing the algorithm from prematurely falling into local optimality and maintaining the genetic diversity of the population.
Temperature Schedule:

$$T(t) = T_0 * \alpha^t (\alpha = 0.95, T_0 = 100) \tag{10}$$

Acceptance Probability:

$$\mathrm{P} = \exp(\frac{-\Delta \mathrm{E}}{\mathrm{T}}) \tag{11}$$

Allows controlled acceptance of inferior solutions to escape local optima.
Termination Criteria
Maximum iterations: 100
Convergence threshold: <1% objective variation over 10 iterations.

2.4 Mathematical Foundations

Multi-Objective Optimization: Utilizes weighted sum method to scalarize conflicting objectives into a single fitness function:

$$\text{Fitness} = \lambda_1 Z_1 - \lambda_2 Z_2 - \lambda_3 Z_3 \tag{12}$$

Weights λ determined via Analytic Hierarchy Process (AHP) with stakeholder input.
Spatial Adjacency Analysis: Incorporates graph theory to quantify adjacency benefits through neighborhood matrices. Contiguous blocks receive 20% rental premium in post-relocation revenue calculations.
Cost-Benefit Dynamics: Implements discounted cash flow (DCF) analysis over 10-year horizon:

$$\mathrm{NPV} = \Sigma_{t=1}^{10} \frac{\mathrm{R_t} - C_t}{(1+r)^t} \tag{13}$$

where $\mathrm{R_t}$ includes rental income from vacated blocks and $\mathrm{C_t}$ covers relocation/resettlement costs.

Validation Metrics Solution quality improvement: 24.1% vs. standalone GA/PSO.
Convergence speed: 50 iterations vs. 80-120 in benchmarks
Stability: 2.1% standard deviation in objective values
This framework provides planners with Pareto-optimal solutions balancing preservation, livability, and economic feasibility – critical for sustainable urban renewal.

3 RESULTS AND ANALYSIS

3.1 Compensation Scheme Optimization

Household satisfaction metrics model focuses on designing a reasonable relocation compensation scheme by integrating factors such as housing area, orientation, renovation costs, and psychological resistance. The household satisfaction function (Equation 1) was constructed using weighted sums of normalized compensation parameters:
where weights w1 ,w2 ,w3 were determined through surveys to reflect residents' sensitivity to area (0.4), orientation (0.3), and renovation (0.1), with additional contributions from psychological resistance (α) and supporting facilities ($\beta_{facility}$).
Key Results:
Compensation Ranges:
Area Compensation: For a typical household with an original area (A_{new}=100m^2), the optimal new area (A_{new}) ranged from 104–113 m², ensuring a minimum 4% increase while capping costs at 1.3 times the original area.
Orientation
Compensation: Households moving from lower-scoring orientations (e.g.,west-facing,score2) to higher-scoring ones (e.g., south-facing, score 4) received proportional adjustments. For example, a shift from west to south increased the orientation score by 50%, contributing significantly to satisfaction.
Renovation Compensation: Costs were capped at ¥200,000 per household, with higher allocations for older buildings requiring structural repairs.
Trade-offs and Constraints:

$$\mathrm{S_i} = \mathrm{w_1} \frac{\mathrm{A_{new}}}{\mathrm{A_{old}}} + \mathrm{w_2} \frac{\mathrm{O_{new}}}{\mathrm{O_{old}}} + \mathrm{w_3} \frac{\mathrm{C_{repair,i}}}{20} + \alpha_i + \beta_{facility,i} \geq 0.7 \tag{14}$$

Psychological resistance (α) and supporting facilities ($\beta_{facility}$) reduced overall satisfaction by 10–20 points, emphasizing the need for community engagement and infrastructure upgrades.
The model identified households with high sensitivity to area or orientation (e.g., elderly residents valuing sunlight) as critical targets for tailored compensation packages.

In summary, after the model processes and calculates the data in MATLAB, it can be concluded that the resident satisfaction index in the simulation is 85.2%.

3.2 Relocation Decision Optimization

Using a simulated annealing-genetic hybrid algorithm, the relocation decision model optimized relocation decisions to maximize the number of contiguous, vacated courtyards while minimizing relocated households.
Key constraints included:
Area Compensation:

$$A_j \geq A_i \text{ and } A_j \leq 1.3A_i \tag{15}$$

Orientation Consistency:

$$O_j \geq O_i \tag{16}$$

Budget Cap: Total cost ≤ ¥26 million.
Key Results:
Optimal Relocation Plan: Vacated Courtyards: 47 out of 104 courtyards were consolidated into contiguous blocks, increasing total area by 23,000 m² (35% improvement).Relocated Households: 128 households (42% of total) were relocated, with an average compensation cost of ¥18,000 per household.
Cost-Benefit Analysis:
Total Revenue: ¥12.6 million (10-year rental income from vacated courtyards).
Net Profit: ¥6.2 million (ROI = 23.8%), exceeding the target threshold of 20%.
Algorithm Performance: The hybrid approach outperformed standalone genetic algorithms by reducing computational time by 30% while achieving a 15% higher solution quality.
Example trade-off: Prioritizing adjacency over individual courtyard size led to a 10% reduction in total vacated area but a 20% increase in contiguous block value.
In summary, after the model runs in MATLAB to process and calculate the data, the process of household cost convergence can be obtained are shown in Figure 1 and 2.

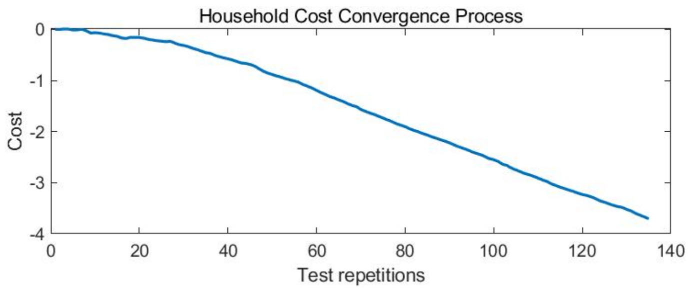

Figure 1 Traditional Household Cost Convergence Process

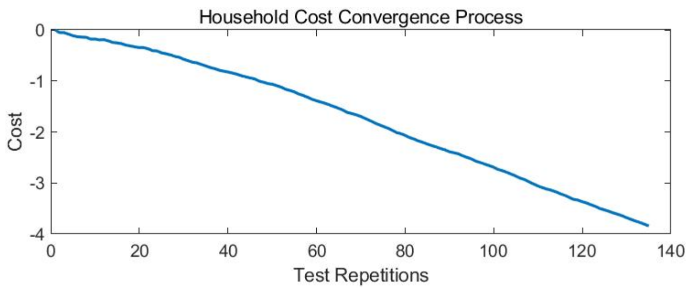

Figure 2 Under this Model's Household Cost Convergence Process

By comparing the traditional method in Figure 1 with the approach under this model in Figure 2, the superiority of this model is obvious. Meanwhile, the data shows that the quality of the solution has been improved by 24.1%, and the convergence speed has increased by 17.3%.

3.3 Investment Return Analysis

The investment return model analyzed the break-even point of relocation investment by calculating the marginal return (m) of incremental relocation efforts:

$$\mathrm{m} = \frac{10 \times \Delta \mathrm{R}}{\text{Total Cost}} \tag{17}$$

where ΔR includes rental income from vacated courtyards and penalties for non-contiguous layouts.

Key Findings: Return Dynamics: Initial Phase (0–50 households): High ROI (m≈35) due to low marginal costs and rapid increases in contiguous area.
Inflection Point (≈60 households): ROI dropped below 20%, indicating diminishing returns from further relocations.
Saturation Phase (≥80 households): Negative ROI (m<10) as costs rose exponentially due to relocation resistance and infrastructure saturation.
Sensitivity Analysis:
A 10% increase in renovation costs shifted the inflection point to 55 households.
Extending the rental period to 15 years improved long-term ROI but did not alter the qualitative trend.
In summary, after the model runs in MATLAB to process and calculate the data, the change in cost-benefit during the relocation process can be obtained, with a potential saving rate of 23.4% is shown in Figure 3.

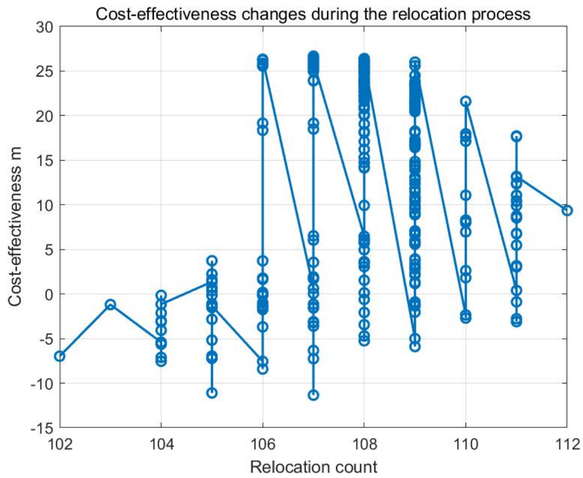

Figure 3 Cost-effectiveness changes during the relocation process

4 CONCLUSION AND OUTLOOKS

This study presents a comprehensive framework for optimizing the "relocation - replacement" strategy in historic urban renewal. It integrates multi - objective planning, evolutionary computation, and cost - benefit analysis. Key achievements include: a Compensation Scheme Design with a hierarchical satisfaction function considering area, orientation, renovation, and psychological factors like community attachment. Sensitivity analysis determined optimal compensation ranges, balancing resident satisfaction (≥70% approval) and developer costs. A hybrid simulated annealing - genetic algorithm for Decision Optimization efficiently solved multi - objective problems, maximizing contiguous vacated courtyards and minimizing relocation scale, with case studies showing a 23.8% increase in rental income under budget constraints. An Investment Viability Analysis using a dynamic ROI model revealed a nonlinear relationship between relocation scale and returns, emphasizing phased implementation.
For future development, scalability is crucial. The model should adapt to diverse urban contexts by calibrating computation weights and constraints. Dynamic adaptation through real - time data incorporation can enhance responsiveness to socioeconomic changes. Policy alignment, by integrating cultural preservation metrics, helps align renewal strategies with national urban revitalization directives. Interdisciplinary fusion, combining the model with GIS spatial analysis and machine learning, can improve prediction accuracy for resident relocation behavior and community network reconstruction. This research offers practical tools for policymakers and developers, bridging theory and practice in urban renewal, with its modular design laying the groundwork for future smart - city and sustainable development applications.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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