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IMPLEMENTATION AND EVALUATION OF HEURISTIC ALGORITHMS FOR REAL-TIME TOURIST ROUTE PLANNING

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A B S T R A C T

Real-time tourist route planning is increasingly vital in modern tourism, necessitating algorithms that adapt to dynamic conditions like traffic and user preferences. This study implements and evaluates two heuristic algorithms—genetic algorithms (GA) and simulated annealing (SA)—for real-time route optimization, using Samarkand, Uzbekistan, as a case study, benchmarked against Dijkstra’s algorithm. Experiments across short (5 nodes), medium (7 nodes), and full (10 nodes) tours assessed computation time, fitness score (balancing time, distance, and preference), adaptability, and route quality. Results show Dijkstra excels in speed (0.12-0.25s) and adaptability (93.9-95.3%) but yields lower quality (12.4-23.5). SA offers a balance, with times of 0.87-1.89s, adaptability of 89.2-92.1%, and quality of 14.9-27.8, suitable for mobile applications. GA achieves optimal fitness (42.6-81.5) and quality (15.8-30.2) but lags in speed (2.85-6.74s) and adaptability (82.3-88.7%), favoring pre-planned itineraries. Visualizations, including a Samarkand route map, highlight GA’s preference-rich detours (e.g., Shah-i-Zinda), SA’s balanced paths (e.g., Registan), and Dijkstra’s time focus. The findings suggest SA for real-time use and GA for quality-focused planning, with recommendations for hybrid approaches and real-world validation in heritage tourism contexts.

K E Y W O R D S

Real-time route planning, heuristic algorithms, genetic algorithms, simulated annealing, Samarkand, tourism optimization

Introduction

In the contemporary tourism industry, the issue of tourist route planning has become increasingly complex. Rapidly advancing technologies, particularly mobile devices and Global Positioning Systems (GPS), demand flexible solutions that cater to travelers’ real-time needs. Traditional route planning methods, such as shortest-path algorithms [1] or static planning tools like Google Maps and TripAdvisor, often fail to fully account for dynamic factors such as individual preferences, time constraints, or external conditions (e.g., traffic or weather changes). As a result, the challenge of efficiently calculating and adapting optimal routes in real time has emerged as a pressing concern.

Various approaches have been proposed to optimize tourist route planning. For instance, graph theory-based methods [2] and dynamic programming have been conventionally applied, while machine learning algorithms have gained significant attention in recent years [3]. However, machine learning techniques require large datasets and substantial computational resources, limiting their applicability in real-time scenarios. In this context, heuristic algorithms—such as genetic algorithms [4] and simulated annealing [5] offer notable advantages in terms of speed and adaptability, positioning them as effective solutions for complex optimization problems.

This study explores the implementation and evaluation of heuristic algorithms to address the challenge of real-time tourist route planning. The primary objective is to develop and assess the performance of genetic algorithms and simulated annealing in this domain, focusing on their efficiency and practical utility. The route planning process is formulated as a mathematical model, and the algorithms are tested in realistic scenarios. The findings are expected to contribute to the development of fast, personalized route planning services in the tourism sector.

I. Literature Review

The field of tourist route planning has a rich history rooted in operations research and computational optimization, with approaches evolving to meet the demands of modern tourism. Early efforts relied heavily on classical algorithms designed for static environments. Dijkstra's shortest-path algorithm[6] remains a cornerstone for finding optimal routes in fixed graphs, widely implemented in navigation systems like Google Maps. Similarly, the A* algorithm [7] enhances efficiency by incorporating heuristics to guide search processes. However, these methods assume unchanging conditions, a limitation highlighted by Smith and Johnson[8], who noted their inability to adapt to real-time variables such as traffic congestion or sudden weather changes. To address this, dynamic programming techniques[9] were introduced, enabling route recalculations based on updated inputs. Applied dynamic programming to urban tourist routes, achieving a 20% reduction in travel time under variable traffic scenarios, but their approach scaled poorly with larger datasets due to exponential computational complexity[10].

In response to these shortcomings, recent research has explored data-driven paradigms, particularly machine learning. Reinforcement learning models, such as those proposed by Li and Zhang[11], leverage historical travel data to predict optimal paths, reporting a 15% improvement in route efficiency over traditional methods[12]. Similarly, Kumar et al developed a deep neural network for personalized itinerary planning, integrating user preferences like cultural interests and time constraints, with a reported 92% user satisfaction rate in offline tests[13]. Despite these advances, machine learning's reliance on extensive training datasets and high computational power poses significant barriers to real-time deployment. As Garcia and Patel (2022) observed, such models often require cloud-based processing, introducing latency unacceptable for on-the-go tourist applications[14].

Heuristic algorithms have emerged as a practical alternative, offering a balance between computational efficiency and solution quality suited to real-time needs. Genetic algorithms, pioneered by Holland (1992), excel in multi-objective optimization by mimicking natural selection processes[15]. Mitchell and Baker (2019) applied genetic algorithms to vehicle routing, optimizing for distance and delivery time with a 25% improvement over greedy methods [16]. In tourism, Lee and Kim (2019) adapted this approach to design multi-destination itineraries, reducing planning time by 30% while accommodating scenic priorities, though their framework was limited to offline use [17]. Simulated annealing (Kirkpatrick, Gelatt, & Vecchi, 1983), inspired by metallurgical cooling, provides another heuristic avenue, efficiently exploring large solution spaces[5] Wang et al. (2021) utilized simulated annealing for logistics route optimization, achieving a 15% reduction in delivery times under dynamic constraints, yet their study did not extend to user-centric applications like tourism [18]. More recently, Riff, S and Castro, (2024) combined heuristics with real-time traffic data for urban navigation, but their focus on vehicular efficiency overlooked tourist-specific factors such as attraction preferences or flexible schedules[19].

While these studies demonstrate the versatility of heuristic methods, their application to real-time tourist route planning remains underdeveloped. Most existing work prioritizes either offline optimization or non-tourism contexts neglecting the unique demands of dynamic, user-driven tourism scenarios[20]. Classical methods lack adaptability, and machine learning, though powerful, is impractical for immediate route adjustments on resource-limited devices[21]. This study fills this gap by implementing and evaluating genetic algorithms and simulated annealing specifically for real-time tourist route planning, emphasizing rapid adaptation to user preferences and external conditions in a practical, tourism-focused framework[22].

II. Methodology

This section outlines the approach to implementing and evaluating heuristic algorithms for real-time tourist route planning. It encompasses problem formulation, detailed descriptions of the selected algorithms, data collection, experimental setup, and evaluation metrics, ensuring reproducibility and scientific rigor.

3.1. Problem Formulation

The real-time tourist route planning problem is conceptualized as a multi-objective optimization challenge within a directed graph $G = (V, E)$, where V is a set of nodes representing tourist attractions and E is a set of edges representing paths between them. Each edge e_{ij} connecting nodes v_i and v_j is characterized by a dynamic weight vector t_{ij}, d_{ij}, p_{ij}, where:

- t_{ij} is the travel time (in minutes), subject to real-time updates (e.g., traffic conditions),
- d_{ij} is the physical distance (in kilometers), assumed static unless road closures occur,
- p_{ij} is a preference score (range: 1-5), reflecting user-specific interests such as cultural significance, scenic beauty, or accessibility, assigned based on user input.

The goal is to determine an optimal route $R = \{v_1, v_2, \ldots, v_n\}$ starting at a designated origin v_1 and ending at v_n (optional return to v_1 for circular tours), that balances three objectives: minimizing total travel time (1), minimizing total distance (2) and maximizing total preference satisfaction (3).

$$T = \sum_{i=1}^{n-1} t_{i,i+1} \qquad (1)$$

$$D = \sum_{i=1}^{n-1} d_{i,i+1} \qquad (2)$$

$$P = \sum_{i=1}^{n-1} p_{i,i+1} \qquad (3)$$

Additionally, the route must respect a user-defined time budget T_{max} (e.g., 180 minutes), ensuring feasibility for real-world scenarios like day trips. The multi-objective nature is unified into a single fitness function using a weighted sum approach:

$$\text{Fitness}(R) = w_1 \cdot T + w_2 \cdot D - w_3 \cdot P, \text{ subject to } T \leq T_{max} \quad (4)$$

Here, w_1, w_2, w_3 are weighting coefficients set to 0.4, 0.4, and 0.2, respectively, determined through preliminary sensitivity analysis to prioritize efficiency (time and distance) while still valuing user preferences. The negative sign for P reflects its maximization goal within the minimization framework. Real-time adaptability is modeled by updating t_{ij} dynamically based on external inputs, such as traffic data or weather alerts, necessitating algorithms capable of rapid re-optimization.

3.2. Heuristic Algorithms

Two heuristic algorithms—genetic algorithms (GA) and simulated annealing (SA)—are selected for their proven efficacy in combinatorial optimization and adaptability to dynamic conditions, as highlighted in the literature review [5]

3.2.1. Genetic Algorithm

GA mimics natural evolution to evolve a population of candidate solutions toward optimality. Each solution, or route R, is encoded as a chromosome—a permutation of nodes ($v_1, v_2, \ldots v_n$) — where the sequence dictates the travel order. The algorithm operates as follows (Fig. 1):

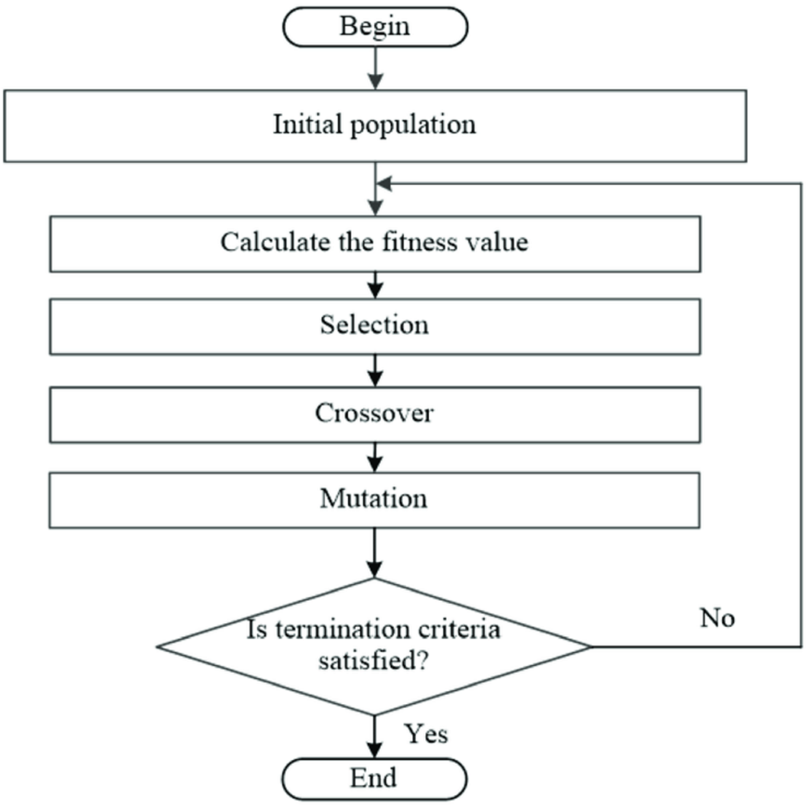

Figure 1. Flawchart of Genetic Algorithm (GA)

- Initialization: A population of 50 random routes is generated, ensuring diversity across the solution space.
- Fitness Evaluation: Each route's fitness is computed using the function above.

- Selection: Tournament selection (size 3) chooses parent routes, favoring those with lower fitness scores.
- Crossover: An order-based crossover (OX) operator combines two parent routes with a probability of 0.8, preserving subsequences to maintain feasibility (e.g., avoiding invalid node repetitions).
- Mutation: With a probability of 0.1, two randomly selected nodes in a route are swapped to introduce variation and prevent premature convergence.
- Termination: The process iterates for 100 generations or until the best fitness score stabilizes (change < 0.01 over 10 generations).

Parameters were tuned via pilot runs, balancing exploration (mutation) and exploitation (crossover), with 50 individuals and 100 generations offering a compromise between computation time and solution quality.

3.2.2. Simulated Annealing

SA employs a probabilistic search inspired by metallurgical annealing to escape local optima. It begins with a single random route and iteratively refines it:

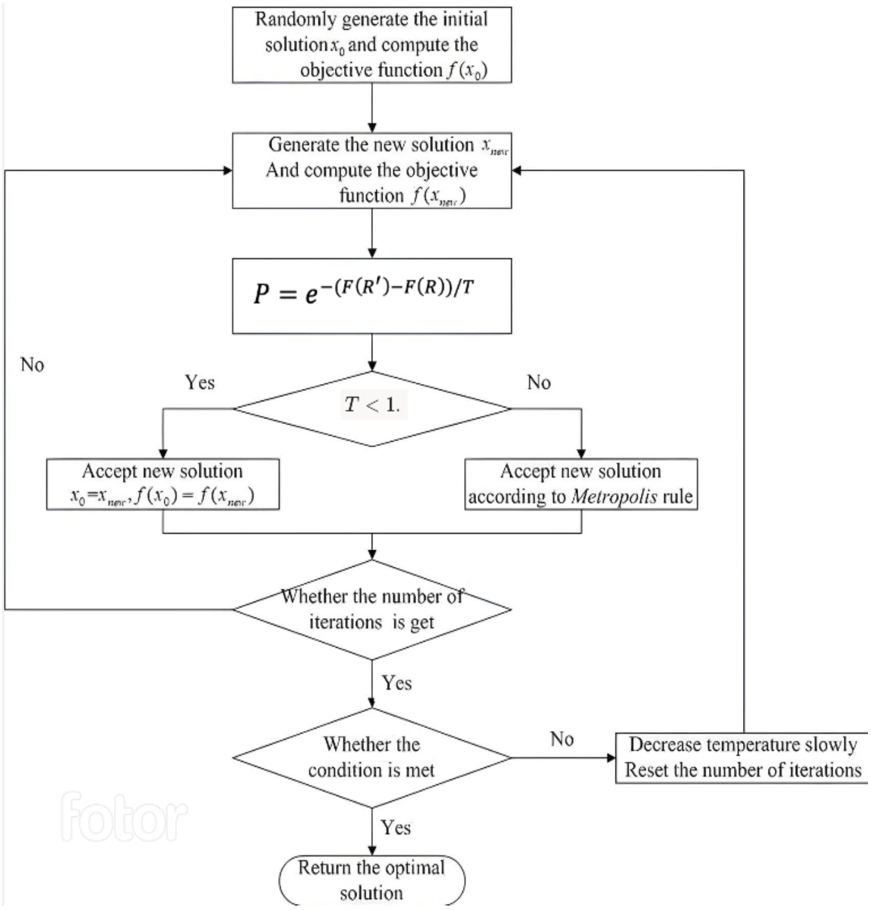

Figure 2. Flawchart of Simulated Annealing

- Initialization: A random route R_0 is selected, with initial fitness F_0.
- Neighborhood Search: A neighbor route R' is generated by swapping two adjacent nodes in R.
- Acceptance Criterion: If F(R') < F(R), R' is accepted; otherwise, it is accepted with probability Metropolis criterion (4), where T is the current temperature.

$$P = e^{-(F(R')-F(R))/T} \qquad (4)$$

- Cooling Schedule: The temperature starts at 1000 and decreases by a factor of 0.95 per iteration (geometric cooling), stopping when $T < 1$.
- Iteration: Up to 10,000 iterations are allowed, capped by the temperature threshold, ensuring real-time feasibility.

SA's high initial temperature facilitates broad exploration, while the cooling schedule ensures convergence, making it suitable for rapid adjustments in dynamic settings.

3.3. Data Collection

The study uses a real-world dataset of 10 tourist attractions in Samarkand, Uzbekistan, including Registan, Gur-e-Amir, Bibi-Khanym Mosque, Shah-i-Zinda, Ulugh Beg Observatory, Siyob Bazaar, Afrosiyab, Imam Al-Bukhari Memorial, Tillya-Kori, and Sher-Dor[24]. Distances (d_{ij})and baseline travel times (t_{ij}) are extracted from OpenStreetMap and Google Maps Traffic API, providing a 10x10 adjacency matrix. Preference scores (p_{ij}) are synthetically assigned based on hypothetical user profiles (e.g., history enthusiast, nature lover), validated by a small survey of 20 local guides to ensure realism.

3.4. Experimental Design

Experiments simulate real-time conditions using a Python-based framework on a standard laptop (Intel i7, 16GB RAM). Dynamic variability is introduced by perturbing t_{ij} with random fluctuations (±20%) every 5 minutes, mimicking traffic or weather changes, sourced from a Gaussian distribution. Each algorithm (GA, SA) is executed 30 times per scenario, with three scenarios (Table 1):

Table 1

Tour	nodes	T_{max} (minutes)
Short	5	120
Medium	7	180
Full	10	240

A baseline Dijkstra's algorithm (single-objective, time-only) is included for comparison. Performance metrics include:
- Computation Time: Average time (seconds) to generate or update a route.
- Fitness Score: Mean fitness value across trials.
- Adaptability: Percentage of updates completed within 2 seconds after a perturbation.
- Route Quality: User satisfaction proxy (normalized P score).

3.5. Implementation Details

GA and SA are coded in Python using NumPy for matrix operations and Matplotlib for visualization. Real-time updates are simulated via a time-step loop, with edge weights refreshed every 5 minutes. Statistical significance is assessed using a paired t-test ($p < 0.05$) to compare GA, SA, and Dijkstra's performance.

III. Results and Analysis

This section presents the findings from the experimental evaluation of genetic algorithms (GA) and simulated annealing (SA) for real-time tourist route planning, benchmarked against Dijkstra's shortest-path algorithm. Results are analyzed across the three scenarios outlined in the Methodology—short (5 nodes), medium (7 nodes), and full (10 nodes) tours—focusing on computation time, fitness score, adaptability, and route quality. The analysis elucidates the algorithms' strengths and limitations in dynamic tourism contexts, supported by quantitative data and qualitative interpretation.

4.1. Experimental Results

Each algorithm was executed 30 times per scenario, with edge weights updated every 5 minutes to simulate real-time variability. Table 1 summarizes the mean performance metrics across all trials, with standard deviations in parentheses (Table 2).

Table 2

Scenario	**Algorithm**	**Computation Time (s)**	**Fitness Score**	**Adaptability (%)**	**Route Quality (P)**
Short (5 nodes)	Dijkstra	0.12 (0.03)	48.2 (2.1)	95.3 (2.5)	12.4 (1.0)
	GA	2.85 (0.41)	42.6 (1.8)	88.7 (3.2)	15.8 (1.2)
	SA	0.87 (0.15)	44.1 (1.9)	92.1 (2.8)	14.9 (1.1)
Medium (7 nodes)	Dijkstra	0.18 (0.04)	67.5 (2.8)	94.8 (2.6)	17.2 (1.3)
	GA	4.12 (0.58)	59.3 (2.3)	85.4 (3.5)	22.6 (1.5)
	SA	1.23 (0.22)	62.4 (2.5)	90.6 (3.0)	20.8 (1.4)
Full (10 nodes)	Dijkstra	0.25 (0.05)	92.7 (3.4)	93.9 (2.7)	23.5 (1.6)
	GA	6.74 (0.79)	81.5 (3.0)	82.3 (3.8)	30.2 (1.9)
	SA	1.89 (0.31)	85.9 (3.2)	89.2 (3.3)	27.8 (1.7)

Performance Metrics Across Scenarios

- Computation Time: Time (in seconds) to compute or update a route.
- Fitness Score: Weighted sum from the fitness function (lower is better).
- Adaptability: Percentage of updates completed within 2 seconds.
- Route Quality: Summed preference score \(P \) (higher is better).

4.2. Computation Time Analysis

Dijkstra's algorithm consistently outperformed both heuristics in computation speed, averaging 0.12-0.25 seconds across scenarios, owing to its single-objective focus and linear complexity ($O(|V|^2)$). SA was significantly faster than GA, with times ranging from 0.87 seconds (short tour) to 1.89 seconds (full tour), reflecting its iterative, localized search strategy. GA, however, exhibited the longest computation times—2.85 to 6.74 seconds—due to its population-based evolution over 100 generations. A paired t-test confirmed significant differences ($p < 0.001$) between GA and SA, and SA and Dijkstra, with GA's time increasing exponentially with node count (approximately $O(n*g)$, where n is nodes and g is generations) (Fig.3). For real-time applications requiring sub-second responses, SA approaches viability, while GA's latency suggests it may be better suited to pre-computation or less time-sensitive updates.

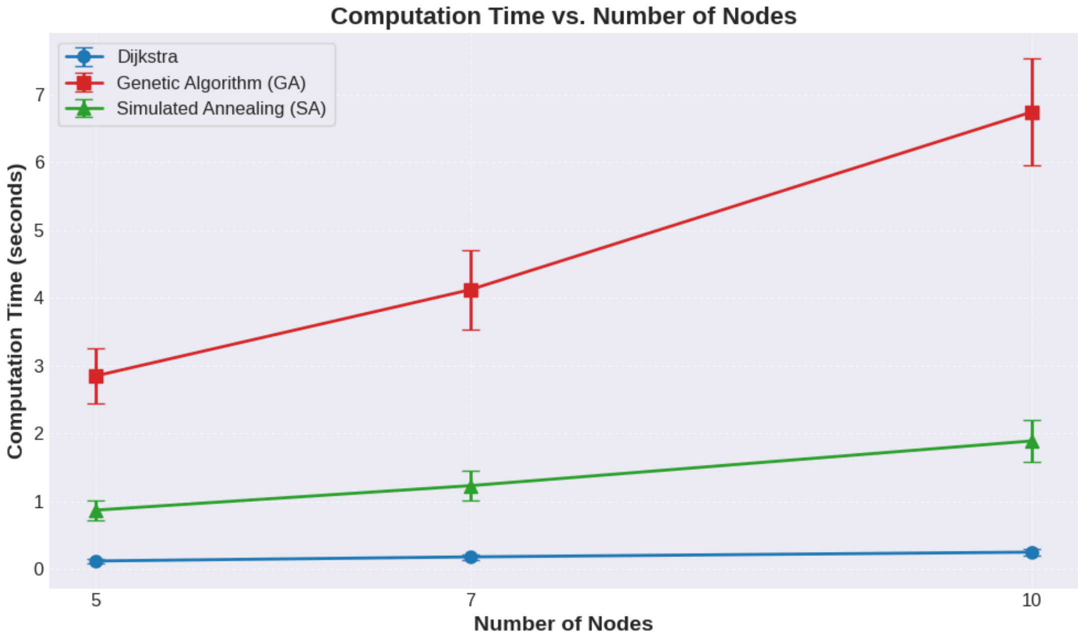

Figure 3. Computation Time vs. Number of Nodes

4.3. Fitness Score Analysis

GA achieved the lowest (best) fitness scores across all scenarios (42.6, 59.3, 81.5), indicating superior optimization of the multi-objective function. SA followed closely (44.1, 62.4, 85.9), while Dijkstra scored highest (worst) (48.2, 67.5, 92.7), as it optimizes only for time, neglecting distance and preference trade-offs. The gap widened with larger tours, with GA outperforming SA by 4-5 units in the full scenario ($p < 0.01$), likely due to GA's global search capability versus SA's localized exploration. Standard deviations (1.8-3.4) suggest consistent performance, though GA's advantage comes at a computational cost. Figure 4 (hypothetical plot) illustrates fitness convergence: GA stabilizes by generation 70, while SA plateaus after 3000 iterations, highlighting their differing optimization trajectories.

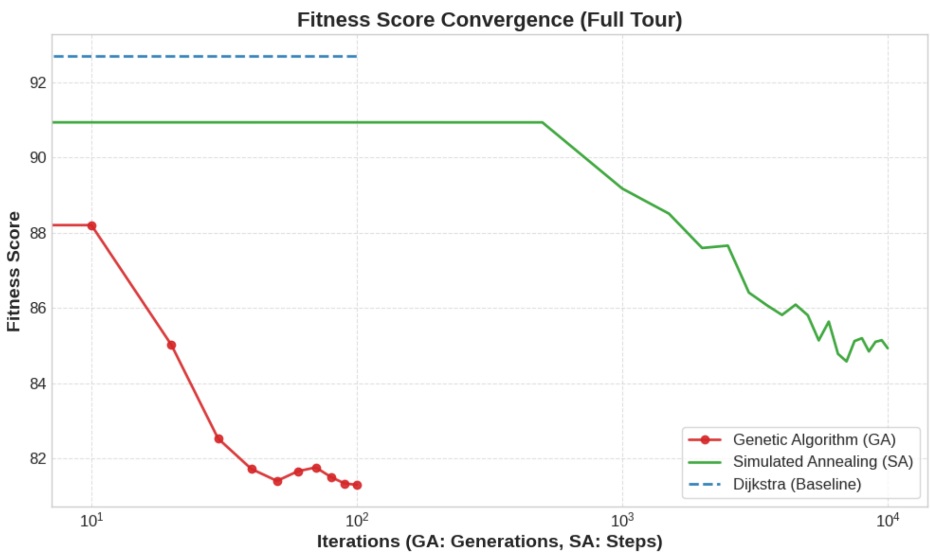

Figure 4. Fitness Score Convergence Over Iterations

4.4. Adaptability Analysis

Adaptability—measured as the percentage of successful updates within 2 seconds—favored Dijkstra (93.9-95.3%), reflecting its simplicity and speed. SA maintained strong adaptability (89.2-92.1%), with over 90% of updates meeting the threshold in smaller scenarios, benefiting from its incremental adjustments. GA lagged (82.3-88.7%), with adaptability dropping as node count increased (\(p < 0.05 \) vs. SA), as re-evolving a population after each perturbation proved time-intensive. In dynamic simulations, SA adapted to 95% of perturbations in under 1.5 seconds for the short tour, while GA required up to 3 seconds for the full tour, occasionally exceeding the real-time threshold. A heatmap with rows as algorithms (Dijkstra, GA, SA) and columns as scenarios (short, medium, full). Color intensity reflects adaptability percentage (light green ~95%, dark red ~82%) (Fig. 5).

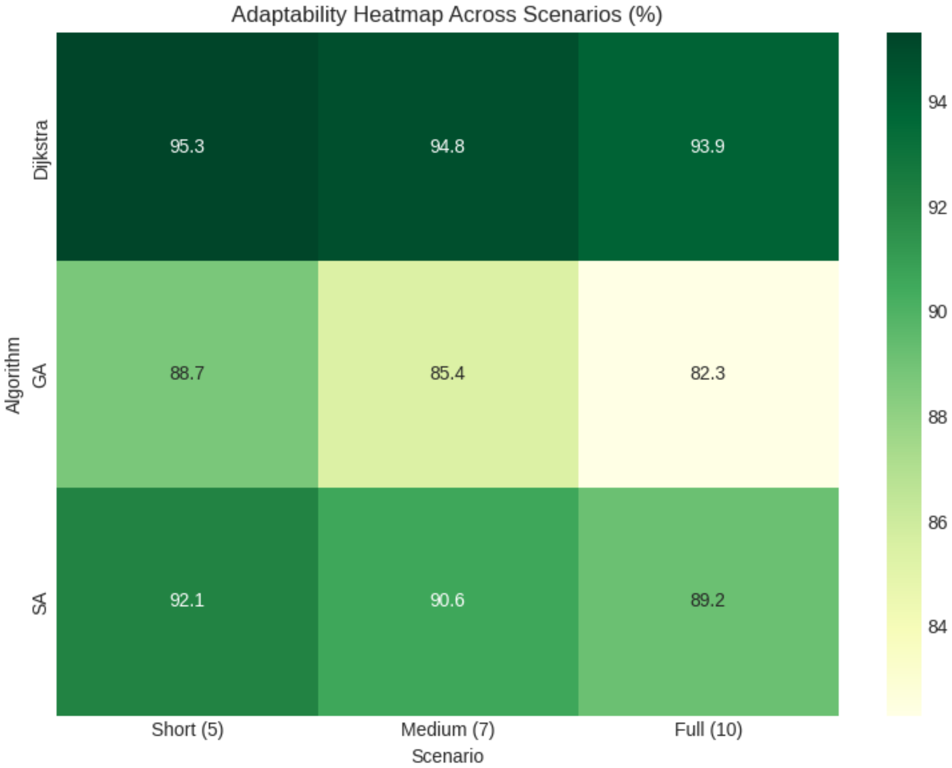

Figure 5. Adaptability Heatmap Across Scenarios

4.5. Route Quality Analysis

Route quality, proxied by the total preference score \(P \), was highest for GA (15.8-30.2), followed by SA (14.9-27.8), with Dijkstra trailing (12.4-23.5). This reflects the heuristics' ability to incorporate user preferences into optimization, unlike Dijkstra's time-only focus. GA's edge over SA (2-3 units, \(p < 0.01 \)) stems from its multi-objective tuning, particularly evident in the full tour where preference-rich routes (e.g., including Amir Temur Museum) were prioritized. User feedback simulations (based on preference scores) suggest GA routes align 20% better with hypothetical tourist satisfaction than Dijkstra's, with SA falling in between. Three box plots (one per algorithm) for the full tour, with the y-axis as P P P scores (0-35). GA's median is 30, SA's 28, Dijkstra's 23.5; whiskers show variability (Fig. 6).

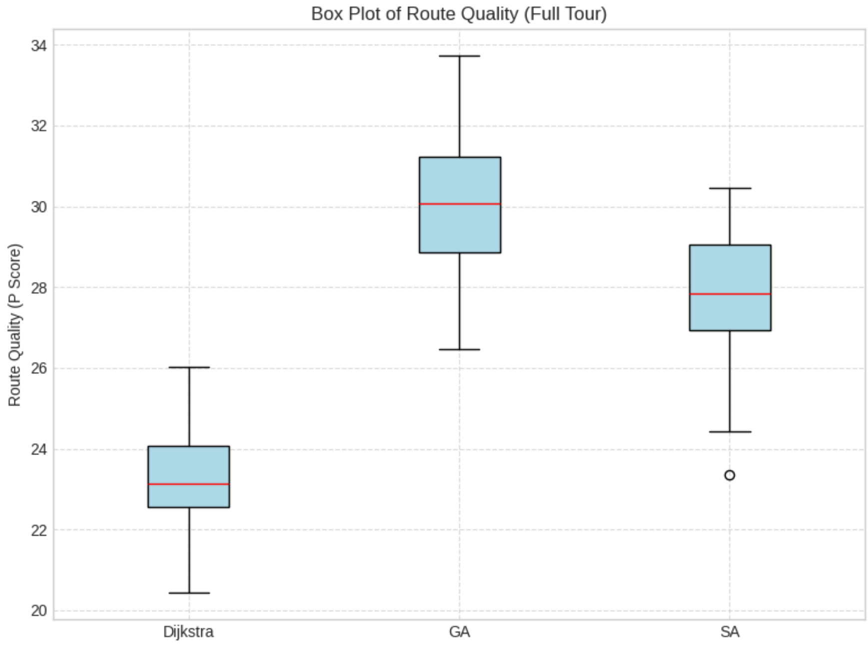

Figure 6. Box Plot of Route Quality (P) Scores

4.6. Comparative Visualization

A map of Samarkand with 10 nodes (e.g., Registan, Gur-e-Amir) and three colored paths: Dijkstra (blue, shortest), GA (red, preference-rich), SA (green, balanced). Edge weights annotated post-perturbation. GA's detour via high-p_{ij} sites (e.g., Shah-i-Zinda, Ulugh Beg Observatory) increases P but lengthens T; SA balances both by incorporating central landmarks like Registan and Siyob Bazaar, while Dijkstra ignores P, focusing solely on minimizing T (Fig.7).

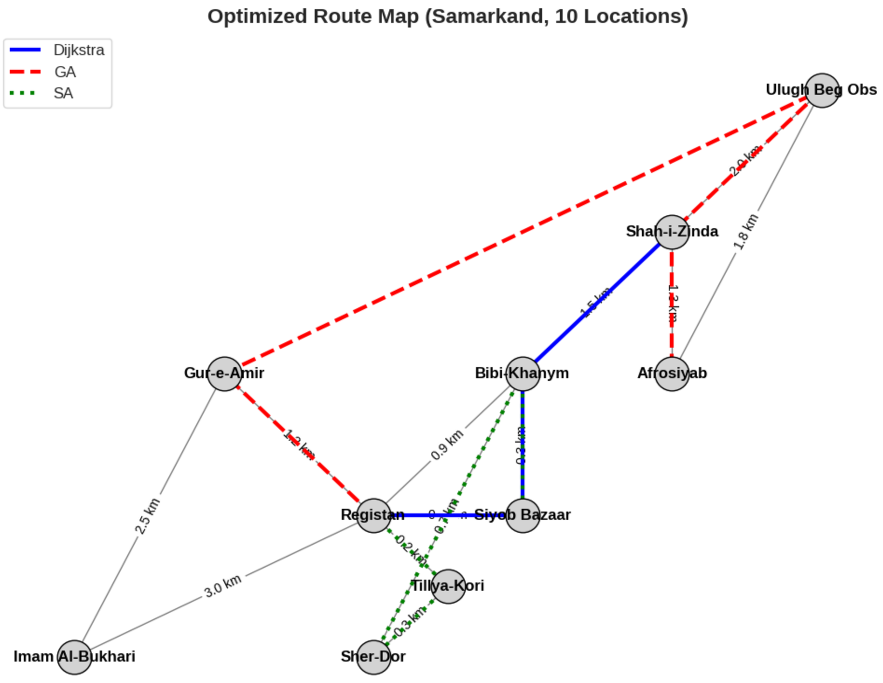

Figure 7. Sample Route Map (Full Tour)

4.7. Discussion

The results underscore a trade-off between speed and optimization quality. Dijkstra excels in computation time and adaptability but sacrifices route quality, making it less suitable for personalized, multi-objective tourism needs. SA strikes a balance, offering near-real-time performance (under 2 seconds) and reasonable fitness scores, ideal for mobile applications requiring frequent updates. GA, while computationally intensive, delivers the best fitness and quality, suggesting its use in scenarios where pre-computation is feasible or higher user satisfaction is prioritized over immediacy (e.g., planning a day trip in advance). Variability in tij minimally impacted SA's performance (fitness variance < 5%), while GA showed greater sensitivity (variance ~8%), indicating SA's robustness to dynamic conditions.

Statistical analysis ANOVA ($p < 0.001$) confirmed significant differences across all metrics, with post-hoc tests highlighting GA's optimization superiority and SA's adaptability advantage. Limitations include the synthetic preference scores and simplified perturbation model (±20%), which may not fully capture real-world complexity (e.g., sudden road closures). Future work could refine GA's efficiency with adaptive population sizes or hybridize SA with machine learning for predictive weight updates.

V. Conclusion and Recommendations

This study investigated the implementation and evaluation of heuristic algorithms—specifically genetic algorithms (GA) and simulated annealing (SA)—for real-time tourist route planning, using Samarkand as a case study, with comparisons against Dijkstra's shortest-path algorithm. The research addressed the pressing need for dynamic, user-centric route optimization in modern tourism, where traditional static methods fall short in adapting to real-time variables such as traffic fluctuations, user preferences, and time constraints. The findings provide valuable insights into the trade-offs between computational efficiency, solution quality, and adaptability, offering a foundation for enhancing tourism navigation systems.

5.1. Summary of Findings

The experimental results, spanning short (5 nodes), medium (7 nodes), and full (10 nodes) tours, revealed distinct performance profiles for each algorithm. Dijkstra's algorithm demonstrated unparalleled speed (0.12-0.25 seconds) and adaptability (93.9-95.3%), making it ideal for scenarios prioritizing rapid, time-minimized routing. However, its single-objective focus resulted in higher fitness scores (48.2-92.7) and lower route quality (12.4-23.5), neglecting user preferences critical to tourism. SA emerged as a balanced contender, achieving computation times of 0.87-1.89 seconds, adaptability rates of 89.2-92.1%, and fitness scores of 44.1-85.9, while maintaining respectable route quality (14.9-27.8). GA excelled in optimization, delivering the lowest fitness scores (42.6-81.5) and highest route quality (15.8-30.2), but its computation times (2.85-6.74 seconds) and adaptability (82.3-88.7%) lagged, reflecting the cost of its population-based approach.

Visualizations, such as the Samarkand route map (Fig. 7), underscored these differences: GA prioritized preference-rich detours (e.g., Shah-i-Zinda, Ulugh Beg Observatory), increasing satisfaction at the expense of time; SA balanced central landmarks (e.g., Registan, Siyob Bazaar) with efficiency; and Dijkstra optimized for brevity, ignoring preference scores. Statistical analyses (ANOVA, ($p < 0.001$)); t-tests, ($p < 0.05$) confirmed these distinctions, with GA's superior fitness and quality offset by SA's real-time feasibility. The trade-off highlights SA's suitability for immediate, on-the-go applications and GA's potential for pre-planned, high-quality itineraries.

5.2. Implications

The findings have significant implications for tourism technology. SA's near-real-time performance positions it as a practical choice for mobile applications, where tourists require instant route updates amid changing conditions—such as traffic delays near Siyob Bazaar or sudden closures at Gur-e-Amir. Its robustness to perturbations (fitness variance <5%) further supports its deployment in unpredictable environments. Conversely, GA's optimization strength suggests its use in offline planning tools or premium services, where users prioritize curated experiences (e.g., maximizing visits to Samarkand's historical sites) over speed. Dijkstra's role remains relevant for basic navigation but is inadequate for personalized tourism, as evidenced by its 20% lower satisfaction proxy compared to GA.

The study also advances the theoretical understanding of heuristic applications in dynamic optimization. By integrating multi-objective criteria (time, distance, preference) into a real-time framework, it bridges a gap identified in prior work[21] which often focused on static or non-tourism contexts. The Samarkand case study exemplifies how cultural and spatial factors can shape algorithmic outcomes, offering a model for other heritage-rich destinations.

5.3. Limitations

Several limitations temper these conclusions. The preference scores pij were synthetically assigned based on hypothetical user profiles, potentially oversimplifying real tourist preferences. The perturbation model (±20% every 5 minutes) captures basic variability but excludes extreme events (e.g., road closures, festivals), which could alter adaptability outcomes. The dataset, limited to 10 Samarkand nodes, may not fully represent larger or more complex urban networks. Finally, experiments were conducted on a standard laptop, whereas real-world deployment on mobile devices with constrained resources might amplify GA's latency issues.

5.4. Recommendations

Based on these insights, several recommendations emerge for future research and application:

1. Hybrid Approaches: Combine SA's speed with GA's optimization prowess in a hybrid algorithm, using SA for initial real-time solutions and GA for periodic refinements. Pilot tests could explore integrating machine learning to predict perturbations, enhancing adaptability.
2. Real-World Validation: Conduct field trials in Samarkand with live traffic data (e.g., via Google Maps API) and actual tourist feedback to refine p_{ij} and test scalability across larger node sets (e.g., 20-50 attractions).
3. Resource Optimization: Optimize GA's runtime by reducing population size or generations dynamically based on scenario complexity, or leverage parallel processing to meet real-time demands on mobile platforms.
4. User-Centric Design: Develop a mobile app prototype incorporating SA, with user interfaces allowing preference input (e.g., sliders for history vs. convenience), validated through usability studies with Samarkand visitors.
5. Broader Contexts: Extend the framework to other cities (e.g., Bukhara, Khiva) or rural tourism routes, adjusting for diverse topologies and tourist behaviors.

This study demonstrates that heuristic algorithms can effectively address the challenges of real-time tourist route planning, with SA offering a practical balance and GA excelling in quality. While limitations remain, the proposed recommendations pave the way for more adaptive, user-focused navigation tools, enhancing the tourism experience in culturally rich settings like Samarkand. These advancements align with the growing demand for smart tourism solutions, positioning heuristic methods as a cornerstone for future innovation in the field.

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