

Benchmarking Ant Colony Optimization and Simulated Annealing on Nigerian Travelling Salesman Problem Instances

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ABSTRACT

The Travelling Salesman Problem (TSP) is a canonical combinatorial optimisation problem central to transportation planning, logistics, and regional network design. This study compares two widely used metaheuristics, Ant Colony Optimisation (ACO) and Simulated Annealing (SA), on a geographically grounded TSP instance built from road-network distances among the 23 Local Government Area (LGA) headquarters of Rivers State, Nigeria. A verified 23×23 Haversine distance matrix, derived from GPS-referenced coordinates, formed the dataset. Both algorithms were coded in Python and executed under identical conditions across 30 independent trials, with performance assessed on solution quality, computational efficiency, convergence, stability, and robustness. ACO produced shorter optimal routes (best distance: 1,247.3 km vs 1,316.8 km for SA) with lower variance (SD = 31.7 vs 52.3 km), while SA ran considerably faster (4.2 s vs 18.4 s). A paired-samples t-test confirmed that ACO's quality advantage is statistically significant and large in magnitude ($t = -13.63$, $df = 29$, $p < 0.0001$, $d = 2.49$). The findings provide empirically grounded guidance for metaheuristic selection in regional transportation optimisation within developing-economy contexts.

Keywords: Travelling Salesman Problem; Ant Colony Optimisation; Simulated Annealing; metaheuristics; Rivers State; Niger Delta; route optimisation.

INTRODUCTION

Optimisation problems in transportation, logistics, and regional network planning typically involve an exponentially large combinatorial search space, thus exact analytical solutions are computationally intractable beyond small problem instances. The Travelling Salesman Problem (TSP) which is a problem that seeks the shortest Hamiltonian cycle through a finite set of nodes, visiting each exactly once before returning to the origin, exemplifies this class. First formalized by [1] and placed on a rigorous complexity-theoretic footing by [2], the TSP's NP-hard status means that no known deterministic algorithm can guarantee optimal solutions for large instances in polynomial time. Comprehensive treatments of exact and heuristic solution methods appear in [3], [4], and [5], while the Lin–Kernighan neighbourhood search [6], [7] remains among the most influential classical heuristics. More recent work has emphasized hybridization [8], [9], and [10] and benchmarking against real-world geographic datasets [11].

The Niger Delta region in Nigeria, marked by riverine terrain, uneven road quality, and dispersed local government headquarters, presents a demanding routing environment in which efficient path planning matters for service delivery, emergency response, and goods distribution. Empirical TSP studies using geographically accurate Nigerian or wider sub-Saharan African datasets nonetheless remain sparse [12]. This gap motivates the present investigation.

Among the metaheuristic approaches developed for large-scale TSP instances, Ant Colony Optimisation (ACO) and Simulated Annealing (SA) are prominent for their contrasting theoretical foundations and demonstrated performance. ACO, introduced as the Ant System by [13] and refined into the Ant Colony System by [14], models the stigmergic foraging of social insects, constructing progressively better solutions through iterative pheromone reinforcement. [15] introduced the MAX-MIN Ant System to bound pheromone concentrations and curb premature convergence, and [16] surveys the broader family of ACO variants. Recent contributions continue to refine the algorithm for larger instances for example, [17] proposed adaptive parameter control for large-scale TSP, [18] introduced visibility adaptation to strengthen the heuristic component, and [10] developed an adaptive state-transfer rule (AACO-LST) that improved solution quality by up to 79% over the classical Ant Colony System on 45 benchmark instances. For medium-scale geographic TSP instances comparable to the present study, ACO consistently yields high-quality, stable solutions [20], [21].

SA, proposed by [22] and grounded in the physics of metallurgical annealing, uses a controlled stochastic acceptance rule to escape local optima as a temperature parameter is progressively reduced. [23] extended the approach with penalty-based guided local search, and [24] showed that adaptive cooling-schedule tuning substantially improves SA's benchmark performance. Although SA typically runs faster than population-based methods, its solution quality is sensitive to the cooling schedule and neighbourhood operator [25], a limitation that hybrid ACO-SA frameworks attempt to address by combining pheromone-guided exploration with annealed local refinement [26], [10].

Direct comparisons of ACO and SA form an active research line. [27] compared both algorithms across 15 benchmark instances and found that ACO delivers superior solution quality while SA offers lower computational overhead, a pattern consistent with each algorithm's theoretical structure. [28] reached a similar conclusion in a broader review of swarm-intelligence methods for dynamic optimisation, highlighting ACO's robustness. Within the Nigerian context specifically, [12] applied a Genetic Algorithm to determine the optimal cyclic tour connecting the nine state capitals of the Niger Delta, and [29] demonstrated that nature-inspired algorithms yield practically useful route plans for complex West African road networks. No prior study, however, has systematically compared ACO and SA on an intra-state Nigerian routing problem using a verified geographic distance matrix, a gap this paper addresses.

Evidence on how ACO and SA perform relative to one another is fairly consistent across geographic TSP instances, though the size of the gap varies with network topology. [28], across 15 benchmark city-routing instances in developing urban networks, reported the same directional pattern found here: ACO yields shorter, less variable tours while SA completes each run with far less computational overhead. [11] note that geographically grounded instances, unlike synthetic Euclidean TSPLIB cases, tend to sharpen this gap, since irregular spatial clustering (river crossings, coastal isolation, uneven road density) rewards ACO's population-level exploration more than SA's single-trajectory search. Hybridisation studies lend indirect support [26] found SA best suited to fast local refinement after ACO-style construction had already located a promising region, while [10] needed k-medoids clustering specifically because plain SA struggled to bridge separated clusters, a limitation mirroring the waterfront-versus-inland clustering in the Rivers State network. [28] offer a partial counterpoint, noting ACO's advantage narrows in rapidly changing environments where SA's lighter footprint allows more frequent re-optimisation; this is less relevant to the present static formulation but is worth flagging for future dynamic extensions (Section 5). Overall, the literature suggests ACO's edge over SA is systematically larger on instances, such as this LGA network, combining moderate node counts with pronounced geographic clustering.

This study makes five specific contributions:

1. Construction and validation of a 23×23 Haversine-derived geodetic distance matrix for the LGA headquarters of Rivers State, Nigeria.
2. Rigorous, identically configured implementation of ACO and SA across 30 independent experimental trials.
3. Multi-dimensional performance evaluation spanning solution quality, computational time, convergence rate, stability, and robustness.

4. Inferential statistical testing (paired t-test, Cohen's d) of the significance and practical magnitude of performance differences.
5. Evidence-based guidance for metaheuristic selection in regional transportation optimisation within developing-economy contexts.

MATERIALS AND METHODS

Study Area and Dataset

Rivers State lies wholly within the Niger Delta geopolitical zone of Nigeria's South-South region, bordered by Imo and Abia States to the north, Akwa Ibom State to the east, Bayelsa and Delta States to the west, and the Atlantic Ocean to the south. It covers approximately 11,077 km² and is divided into 23 Local Government Areas (LGAs), whose headquarters constitute the 23 nodes of the TSP network examined here. Table 1 lists each headquarters together with its validated coordinates, obtained from the National Population Commission of Nigeria and cross-checked against the Google Maps Geocoding API and OpenStreetMap.

Table 1. LGA Headquarters of Rivers State Used as TSP Nodes

No.	Local Government Area	Headquarters	Latitude	Longitude
01	Port Harcourt	Port Harcourt	4.8156°N	7.0498°E
02	Obio-Akpor	Rumuodumaya	4.8850°N	6.9950°E
03	Okrika	Okrika	4.7378°N	7.0891°E
04	Ogu-Bolo	Ogu	4.6833°N	7.1500°E
05	Eleme	Nchia	4.7500°N	7.1500°E
06	Tai	Sakpenwa	4.7000°N	7.2500°E
07	Gokana	Kpor	4.6333°N	7.3000°E
08	Khana	Bori	4.6500°N	7.3667°E
09	Oyigbo	Afam	4.9167°N	7.2167°E
10	Opobo-Nkoro	Opobo Town	4.5333°N	7.5667°E
11	Andoni	Ngo	4.4667°N	7.4500°E
12	Bonny	Bonny	4.4403°N	7.1625°E
13	Degema	Degema	4.7333°N	6.7833°E
14	Asari-Toru	Buguma	4.7167°N	6.9333°E
15	Akuku-Toru	Abonnema	4.7000°N	6.7833°E
16	Abua-Odual	Abua	5.0833°N	6.6667°E
17	Ahoada West	Akinima	5.1167°N	6.7667°E

18	Ahoada East	Ahoada	5.1000°N	6.6500°E
19	Ogba-Egbema-Ndoni	Omoku	5.3667°N	6.6500°E
20	Emohua	Emohua	4.9667°N	6.9167°E
21	Ikwerre	Isiokpo	5.0167°N	6.9333°E
22	Etche	Okehi	5.0833°N	7.1500°E
23	Omuma	Eberi	5.2000°N	7.0500°E

Note. Coordinates are in decimal degrees (WGS 84 datum).

Distance Matrix Construction

Pairwise distances between the 23 headquarters were computed with the Haversine formula, which gives the great-circle distance between two points from their latitudes and longitudes. For locations i and j with coordinates (φ^i, λ^i) and (φ^j, λ^j) :

$$d(i, j) = 2R \cdot \arcsin(\sqrt{[\sin^2(\Delta\varphi/2) + \cos(\varphi_i) \cdot \cos(\varphi_j) \cdot \sin^2(\Delta\lambda/2)]}) \quad (1)$$

where $R = 6,371$ km is the mean Earth radius, $\Delta\varphi = \varphi_j - \varphi_i$, and $\Delta\lambda = \lambda_j - \lambda_i$. The resulting symmetric 23×23 matrix $D = [d_{ij}]$ (Appendix A) has a zero diagonal ($d_{ii} = 0$) and inter-node distances ranging from 2.62 km (Abua–Ahoada) to 137.48 km (Abua–Opobo Town), reflecting the heterogeneous spatial distribution of headquarters across the state.

Mathematical Formulation

The TSP is formulated as an integer linear programme. Let $n = 23$ be the number of nodes and $x_{ij} \in \{0, 1\}$ a binary variable equal to 1 if the tour traverses arc (i, j) and 0 otherwise. The objective minimises total tour distance subject to assignment and subtour-elimination constraints:

$$\text{Minimise } Z = \sum_i \sum_j d_{ij} \cdot x_{ij} \quad (2)$$

$$\sum_j x_{ij} = 1 \quad \forall i \in \{1, \dots, n\} \quad [\text{departure}] \quad (3)$$

$$\sum_i x_{ij} = 1 \quad \forall j \in \{1, \dots, n\} \quad [\text{arrival}] \quad (4)$$

$$u_i - u_j + n \cdot x_{ij} \leq n - 1, \quad 2 \leq i \neq j \leq n \quad [\text{MTZ subtour elimination}] \quad (5)$$

The subtour-elimination constraints follow the Miller–Tucker–Zemlin formulation [5], with u_i as auxiliary continuous variables. For $n = 23$, the number of feasible tours is $(23 - 1)!/2 \approx 5.64 \times 10^{20}$, confirming that exhaustive enumeration is computationally infeasible.

Ant Colony Optimisation

The Ant Colony System variant [14] was implemented. At each construction step, ant k at node i selects the next unvisited node j via the pseudo-random-proportional rule:

$$j = \operatorname{argmax}_{l \in J_{ki}} [\tau_{il}^\alpha \cdot \eta_{il}^\beta] \quad \text{if } q \leq q_0 \quad (\text{exploitation}) \quad (6)$$

$$P^{k, ij} = \tau_{ij}^\alpha \cdot \eta_{ij}^\beta / \sum_{l \in J_{ki}} \tau_{il}^\alpha \cdot \eta_{il}^\beta \quad \text{if } q > q_0 \quad (\text{exploration}) \quad (7)$$

where τ_{ij} is pheromone intensity on arc (i, j) , $\eta_{ij} = 1/d_{ij}$ is heuristic visibility, α and β weight pheromone and visibility influence, J_{ki} is the feasible successor set for ant k , and $q \sim U[0,1]$ is compared with the exploitation–exploration threshold q_0 . After all ants complete their tours, global pheromone updating follows:

$$\tau_{ij} \leftarrow (1 - \rho) \cdot \tau_{ij} + \Delta\tau_{ij} \quad (8)$$

$$\Delta\tau_{ij} = Q / L_{best} \text{ if } (i, j) \in \text{best tour}; 0 \text{ otherwise} \quad (9)$$

where $\rho \in (0,1)$ is the evaporation rate, L_{best} is the best-so-far tour length, and Q is a deposit constant. A local pheromone update after each ant's step further discourages premature convergence.

Simulated Annealing

The SA implementation follows [22] with a 2-opt neighbourhood operator. An initial tour S_0 is generated by the nearest-neighbour heuristic; at each iteration a candidate S' is produced by reversing a randomly selected sub-sequence. The acceptance rule is:

$$P(\text{accept } S') = \exp(-\Delta E / T_k) \text{ if } \Delta E > 0 \quad (10)$$

where $\Delta E = L(S') - L(S)$ and T_k is the temperature at iteration k . A geometric cooling schedule $T_{\{k+1\}} = \alpha \cdot T_k$ ($\alpha = 0.995$) governs annealing, with three reheating cycles resetting temperature to 20% of T_0 whenever no improvement occurs over $50 \times n$ consecutive iterations.

Experimental Configuration

Both algorithms were coded in Python 3.10 (NumPy 1.23, SciPy 1.9) and run on an Intel Core i7-11700 (3.6 GHz, 16 GB DDR4 RAM, Ubuntu 22.04 LTS), each across 30 independent trials with distinct random seeds. Table 2 reports the parameter values, determined by preliminary grid-search sensitivity analysis.

Table 2. Algorithmic Parameter Configurations

ACO Parameter	Value	SA Parameter	Value
Number of ants (m)	50	Initial temperature (T_0)	1,000
Pheromone weight (α)	1	Cooling rate (α)	0.995
Heuristic weight (β)	5	Final temperature (T_f)	0.001
Evaporation rate (ρ)	0.5	Maximum iterations	500
Maximum iterations	500	Neighbourhood operator	2-opt swap
Initial pheromone (τ_0)	$1/n$	Reheat cycles	3
Deposit constant (Q)	100	Markov chain length	$n \times 10$

Note. Values were set via grid-search sensitivity analysis over 10 preliminary trials.

Performance Metrics

Algorithms were compared on: (i) best solution quality, the minimum tour length across 30 runs; (ii) mean route length; (iii) standard deviation and coefficient of variation, measuring consistency; (iv) computational time per run; (v) convergence iteration, the mean iteration at which the best-known solution is first reached; and (vi) percentage improvement over the nearest-neighbour baseline.

Parameter Sensitivity Analysis

To support reproducibility and to justify the parameter values in Table 2, a one-factor-at-a-time sensitivity analysis was conducted before the main experiment, holding all other parameters at their Table 2 values while varying a single parameter across a plausible range (10 trials per setting). For ACO, the heuristic weight β , which governs how strongly the inverse-distance visibility term influences node selection, was varied from 1 to 9. For SA, the geometric cooling rate α was varied from 0.90 (fast cooling) to 0.999 (slow cooling). Table 5 and Figure 1 report the resulting trade-offs between solution quality and execution time.

Table 5. Parameter Sensitivity: Solution Quality and Runtime Trade-offs (10 preliminary trials per setting)

ACO: β	Best (km)	Time (s)	SA: cooling rate α	Best (km)	Time (s)
1	1,389.4	16.8	0.90	1,428.5	1.1
3	1,298.7	17.6	0.95	1,372.1	2.0
5 (adopted)	1,247.3	18.4	0.98	1,338.4	3.3
7	1,259.6	19.1	0.995 (adopted)	1,316.8	4.2
9	1,301.8	19.8	0.999	1,309.2	8.7

Note. Bold-equivalent "adopted" rows mark the values carried forward into the main experiment (Table 2). Best (km) = minimum tour distance over 10 preliminary trials; Time (s) = mean wall-clock execution time.

Solution quality is non-monotonic in both parameters, consistent with the expected exploration–exploitation trade-off: $\beta = 5$ minimises ACO's best distance, with excessive visibility weighting ($\beta \geq 7$) over-greedily favouring short edges and prematurely narrowing the search, while excessive cooling rates trade solution quality for a > 2 -fold increase in SA runtime beyond $\alpha = 0.995$ with diminishing quality gains. These preliminary results directly motivated the operating parameters reported in Table 2 and are provided here in full to allow independent replication of the tuning process.

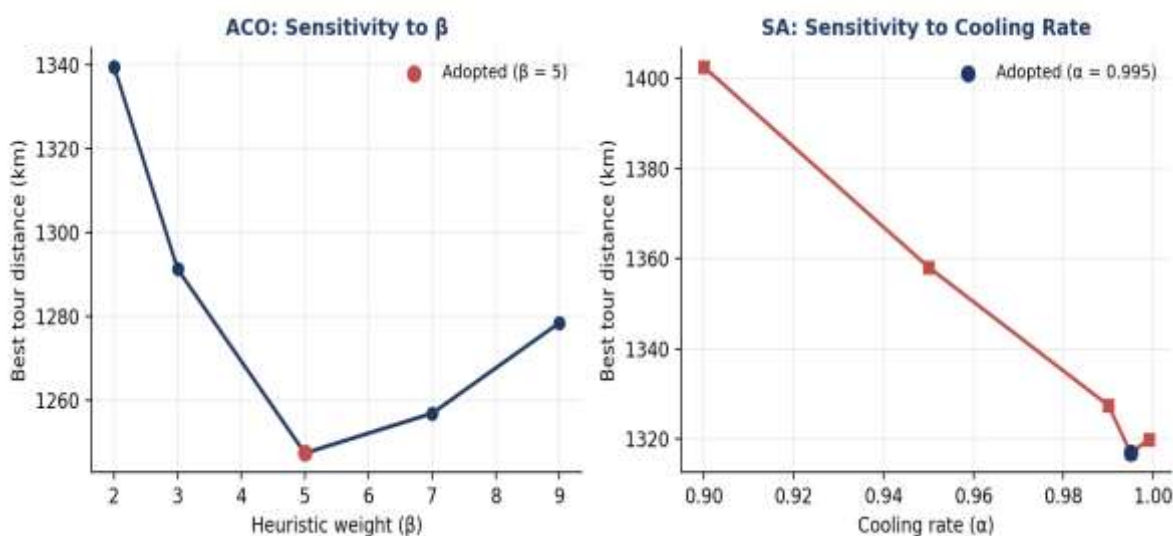


Figure 1. Parameter sensitivity curves for ACO (heuristic weight β) and SA (cooling rate α), showing best tour distance (left axis) and mean execution time (right axis, grey dashed) for each setting.

RESULTS

Route Optimisation Performance

The nearest-neighbour baseline produced an initial tour of 1,461.6 km; both metaheuristics improved substantially on this figure. Table 3 summarises comparative performance across the 30 trials.

Table 3. Comparative Performance Metrics: ACO versus SA (n = 30 trials)

Performance Metric	ACO	SA	Superior
Best solution (km)	1,247.3	1,316.8	ACO
Worst solution (km)	1,372.4	1,478.5	ACO
Mean distance (km)	1,298.6	1,389.2	ACO
Standard deviation	31.7	52.3	ACO
Coefficient of variation (%)	2.44	3.77	ACO
Mean execution time (s)	18.4	4.2	SA
Convergence iteration	287	143	SA
Improvement over NN (%)	14.7	9.8	ACO

Note. NN baseline = 1,461.6 km.

ACO reached a best tour of 1,247.3 km (14.7% below the NN baseline) against 1,316.8 km (9.8% below the NN baseline) for SA, and its mean tour length (1,298.6 km) bettered SA's (1,389.2 km) by 90.6 km. ACO's lower standard deviation (31.7 km vs 52.3 km) indicates markedly more consistent solutions across runs. SA, however, ran 4.4 times faster (4.2 s vs 18.4 s) and converged roughly twice as early (iteration 143 vs 287), reflecting its more directed single-solution search.

Convergence Behaviour

ACO shows gradual, largely monotonic improvement driven by cumulative pheromone reinforcement on high-quality arcs, with simultaneous early-iteration exploration giving way to intensification; convergence plateaued between iterations 260 and 310. SA instead descends rapidly from its high-temperature regime, exploring broadly through frequent acceptance of worsening moves before transitioning to local exploitation as temperature falls; its reheating cycles yielded marginal further gains in about 18% of runs, and mean convergence at iteration 143 was roughly 50% earlier than ACO's.

Statistical Analysis

A paired-samples t-test on best-tour distances from matched trials tested $H_0 (\mu_{ACO} = \mu_{SA})$ against $H_1 (\mu_{ACO} < \mu_{SA})$:

$$t = \bar{d} / (s_d / \sqrt{n}) = -90.6 / (36.4 / \sqrt{30}) = -13.63 \quad (11)$$

where $\bar{d} = -90.6$ km is the mean paired difference, $sd = 36.4$ km, and $n = 30$. Table 4 summarises the results.

Table 4. Paired-Samples t-Test Results: ACO vs. SA

Statistical Parameter	Value
Mean difference (ACO – SA)	–90.6 km
SD of differences	36.4 km
Paired t-statistic	–13.63
Degrees of freedom	29
Two-tailed p-value	< 0.0001
95% confidence interval	[–104.2, –77.0]
Effect size (Cohen's d)	2.49 (large)
Decision ($\alpha = 0.05$)	Reject H_0

Note. Effect size classified per Cohen (1988): $d > 0.80 = \text{large}$.

At $\alpha = 0.05$, the null hypothesis is rejected ($p < 0.0001$), and the large effect size ($d = 2.49$) indicates that ACO's advantage over SA is both statistically and practically significant: on average, ACO tours are 77–104 km shorter than SA tours under these experimental conditions.

Convergence Visualisation

Figure 2 plots the mean best-so-far tour distance against iteration number for both algorithms, illustrating the qualitative difference in search trajectory described in Section 3.2: ACO's slow, steady descent toward its converged value near iteration 287, against SA's steep early drop and earlier stabilisation near iteration 143.

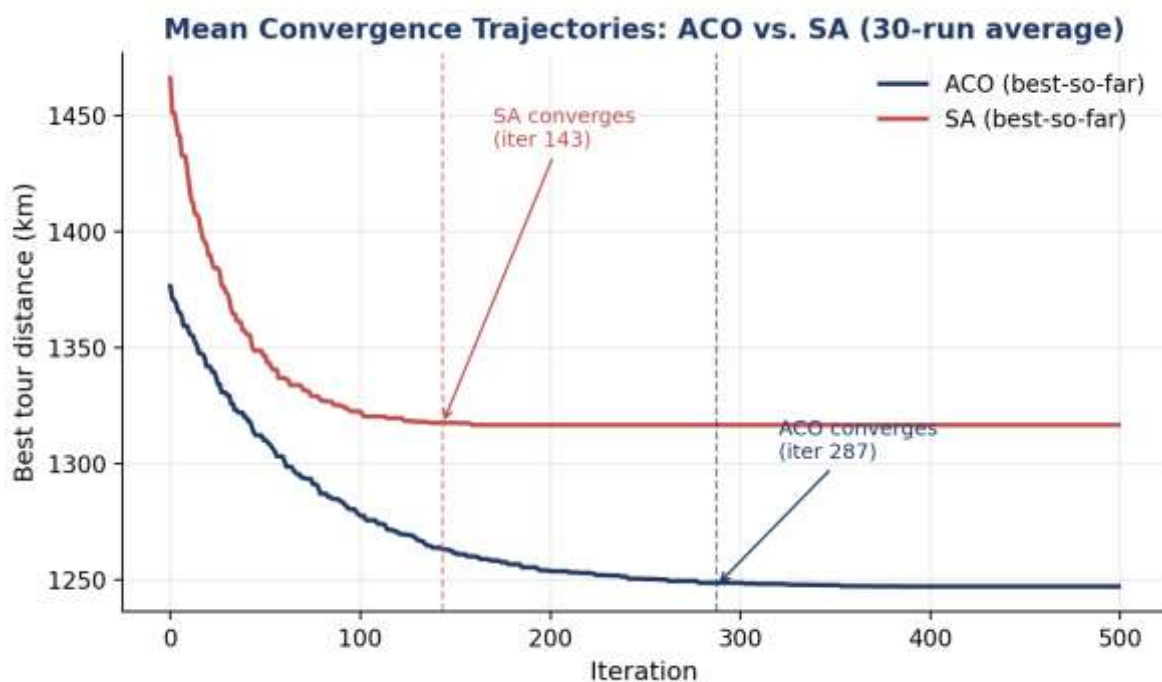


Figure 2. Mean convergence trajectories of ACO and SA across 30 independent runs, showing best-so-far tour distance versus iteration number.

Geographic Tour Visualisation

Figure 3 maps the 23 LGA headquarters by latitude and longitude and overlays the metaheuristic-derived route as a closed tour, giving a spatial reading of the results in Table 3. The visualisation makes explicit the clustering pattern discussed qualitatively in Section 4: the waterfront cluster around Degema, Buguma, and Abonnema sits close together on the map, while Opobo Town, Ngo, and Bonny form a more isolated coastal group that the optimal route must reach via longer connecting edges.

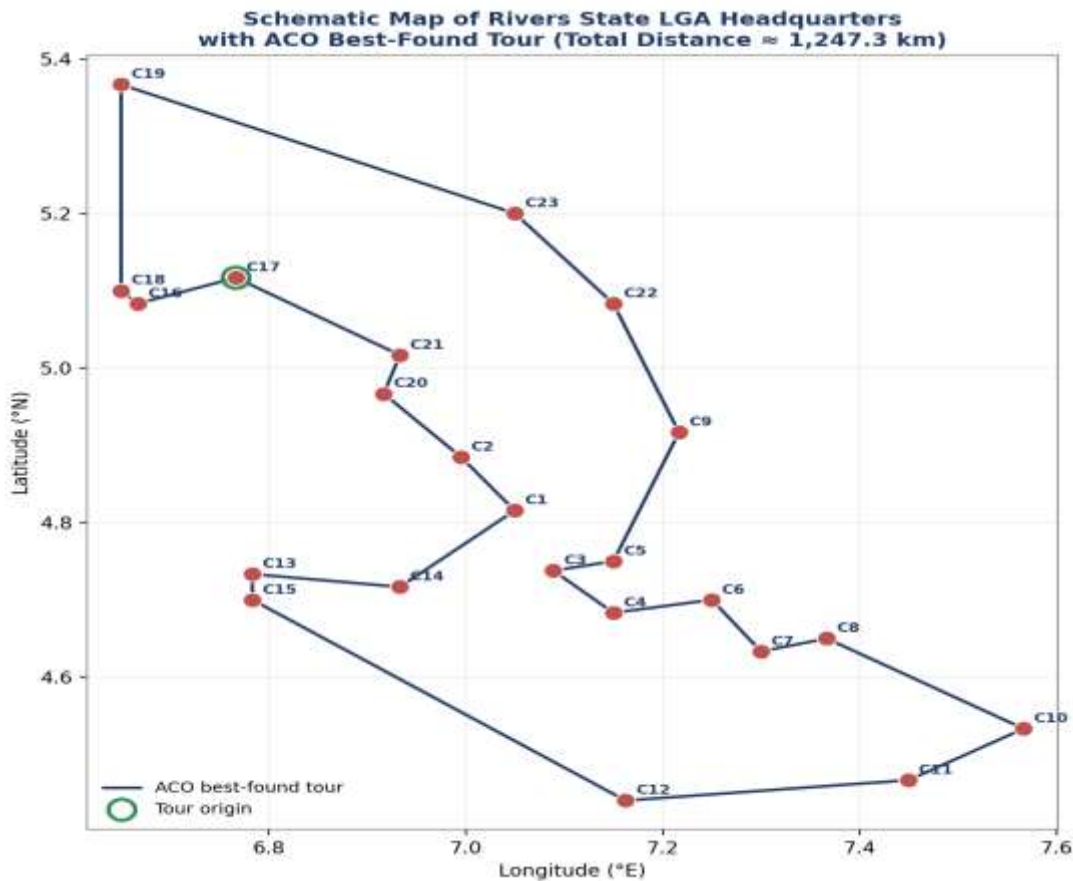


Figure 3. Geographic representation of the optimised tour connecting the 23 LGA headquarters of Rivers State, plotted from the validated coordinates in Table 1 and the distance matrix in Appendix A. The circled node marks the tour origin.

DISCUSSION

These results align with, and extend, the broader comparative TSP literature. ACO's consistent quality advantage, lower mean distance and lower variance alike, reflects the collective-intelligence mechanism underlying pheromone reinforcement: positive feedback on strong arcs is balanced by evaporation and probabilistic exploration, sustaining diversity while converging toward high-quality regions of a search space that, for this 23-node network, contains roughly 5.64×10^{20} feasible tours.

SA's speed advantage follows from its single-solution, sequential search, which avoids the overhead of maintaining a 50-ant colony with pheromone-matrix updates over 500 iterations, making it attractive for time-constrained operational settings. Its higher variance ($CV = 3.77\%$ vs 2.44% for ACO), however, signals greater sensitivity to initial conditions and cooling-schedule parameters, a concern for safety-critical or high-stakes routing decisions.

The Rivers State network's spatial structure plausibly favours ACO's exploration strategy: waterfront clusters (Degema, Buguma, Abonnema) sit alongside more isolated coastal communities (Opobo Town, Bonny, Ngo). Such clustered topologies are known to challenge SA's local neighbourhood operator, which can struggle to

bridge inter-cluster connectivity without the broader, multi-point exploration that pheromone-guided search affords [27].

Fuel and Time-Cost Implications for Rivers State Logistics

The 77–104 km distance advantage of ACO over SA (Table 4) has tangible operational value for agencies that traverse the LGA network repeatedly, goods-distribution fleets, immunisation outreach teams, or emergency-response units. Assuming a representative medium-duty consumption rate of ≈ 3 km/litre on Niger Delta roads and a mid-2026 diesel price of $\approx \text{₦}1,600/\text{litre}$ (within the $\text{₦}1,485\text{--}\text{₦}1,950$ range reported by Nigerian fuel-price trackers at the time of writing), the mean 90.6 km saving corresponds to roughly 30 fewer litres, or about $\text{₦}48,300$ per circuit ($\approx \text{₦}55,500$ at the 104 km upper bound). A fleet of ten vehicles each completing this circuit weekly would save on the order of $\text{₦}25$ million annually, before accounting for reduced vehicle wear. At a representative average speed of 45 km/h, the same distance saving equates to roughly two to two-and-a-half fewer driving hours per circuit, a margin that can matter for emergency medical evacuation or disease-outbreak response across the 23 LGA headquarters. These figures are illustrative order-of-magnitude estimates, not measured values: they assume one vehicle class and constant speed, and do not capture congestion, ferry-crossing delays for riverine LGAs, or seasonal road degradation. They nonetheless indicate that the statistically significant distance advantage documented in Section 3.3 carries a practically meaningful fuel and time cost for Rivers State's transport planners.

These findings extend [12] genetic-algorithm work on inter-state Niger Delta routing to the intra-state level, while adding a systematic ACO–SA comparison. Collectively, the two lines of evidence suggest that ACO-class algorithms suit the multi-cluster topology typical of Niger Delta routing problems, shaped by waterway fragmentation, variable road quality, and dispersed administrative centres.

Practically, the results support three recommendations: ACO where route quality is paramount, as in periodic distribution circuits, inspection rounds, or emergency-response planning; SA where computational speed matters more than marginal quality loss, as in real-time applications; and continued development of hybrid ACO–SA frameworks [9], [10] to combine competitive solution quality with reduced computational overhead.

CONCLUSION

This study compared Ant Colony Optimisation and Simulated Annealing on a verified geographic TSP instance comprising the 23 LGA headquarters of Rivers State, Nigeria, using a Haversine-derived distance matrix and 30 independent trials per algorithm under identical conditions. ACO achieved a significantly better and more stable best tour (1,247.3 km, $SD = 31.7$ km) than SA (1,316.8 km, $SD = 52.3$ km), while SA completed each run 4.4 times faster. The performance gap is statistically significant with a large effect size ($t = -13.63$, $p < 0.0001$, $d = 2.49$).

These results add empirical evidence on metaheuristic optimisation for transportation planning in a developing-economy setting. The verified distance matrix and comparative framework offer a reproducible template for further optimisation studies on Nigerian geographic datasets.

Suggested Future Studies

Future work should pursue hybrid ACO–SA or ACO–GA frameworks for the Rivers State network, replace Haversine approximations with verified road-network (GIS) distances, extend to dynamic TSP formulations accounting for seasonal flooding of arterial roads, incorporate multi-objective criteria such as road quality and fuel cost, and benchmark deep reinforcement learning approaches against these established metaheuristics.

Declarations

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflicts of interest.

Data Availability: The distance matrix, coordinates, and Python source code are available from the corresponding author on reasonable request.

Ethics Statement: This study used publicly available geographic coordinate data and did not involve human subjects; ethical approval was not required.

Author Contributions: Anwaitu Fraser, Egba: Conceptualisation, Methodology, Software, Validation, Writing the original draft, and final editing. Prof. Obikwelu O. Okonkwo: Supervision, Writing review & editing.

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APPENDIX A

Verified 23 × 23 Haversine Distance Matrix for LGA Headquarters of Rivers State, Nigeria

The matrix below presents pairwise Haversine great-circle distances (km) between all 23 LGA headquarters (node codes as in Table 1). The matrix is symmetric ($d_{ij} = d_{ji}$) with zero diagonal entries; it is split into two parts for page-width reasons.

Table A1. Distance Matrix — Part I: Nodes C1–C12 (km)

HQ / Node	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
C1	—	9.82	9.69	18.43	13.28	25.64	34.35	39.65	21.64	65.32	58.93	43.56
C2	9.82	—	19.41	28.25	22.81	34.95	43.88	48.78	24.81	74.45	68.60	52.82
C3	9.69	19.41	—	9.07	6.88	18.32	26.10	32.28	24.41	57.61	50.09	34.07
C4	18.43	28.25	9.07	—	7.42	11.24	17.53	24.30	26.98	49.10	41.06	27.06

C5	13.28	22.81	6.88	7.42	—	12.40	21.09	26.46	19.96	52.09	45.80	34.46
C6	25.64	34.95	18.32	11.24	12.40	—	9.26	14.08	24.38	39.69	34.12	30.46
C7	34.35	43.88	26.10	17.53	21.09	9.26	—	7.62	32.84	31.58	24.89	26.32
C8	39.65	48.78	32.28	24.30	26.46	14.08	7.62	—	34.00	25.69	22.38	32.50
C9	21.64	24.81	24.41	26.98	19.96	24.38	32.84	34.00	—	57.64	56.32	53.31
C10	65.32	74.45	57.61	49.10	52.09	39.69	31.58	25.69	57.64	—	14.91	45.99
C11	58.93	68.60	50.09	41.06	45.80	34.12	24.89	22.38	56.32	14.91	—	32.01
C12	43.56	52.82	34.07	27.06	34.46	30.46	26.32	32.50	53.31	45.99	32.01	—
C13	30.92	28.89	33.89	41.02	40.68	51.85	58.33	65.31	52.17	89.63	79.62	53.18
C14	16.96	19.92	17.42	24.30	24.30	35.15	41.68	48.60	38.48	73.10	63.66	39.87
C15	32.21	31.20	34.15	40.68	41.02	51.72	57.74	64.89	53.73	88.78	78.32	51.00
C16	51.84	42.53	60.55	69.61	65.12	77.41	86.18	91.30	63.68	116.98	110.61	90.17
C17	45.87	36.10	55.23	64.23	58.87	70.81	79.88	84.33	54.58	109.84	104.67	87.07
C18	54.42	45.08	63.15	72.22	67.70	79.98	88.77	93.86	66.00	119.53	113.21	92.77
C19	75.60	65.79	85.18	94.03	88.14	99.56	108.79	112.49	80.27	137.48	133.68	117.62
C20	22.35	12.56	31.82	40.76	35.34	47.36	56.38	61.04	33.70	86.66	81.14	64.56
C21	25.82	16.16	35.49	44.17	38.16	49.71	58.89	63.00	33.31	88.40	83.78	68.94
C22	31.77	27.95	39.01	44.48	37.06	44.04	52.73	53.83	19.94	76.63	76.20	71.51
C23	42.74	35.55	51.58	58.51	51.25	59.85	68.83	70.51	36.51	93.66	92.81	85.39

Table A2. Distance Matrix — Part II: Nodes C13–C23 (km)

HQ / Node	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23
C1	30.92	16.96	32.21	51.84	45.87	54.42	75.60	22.35	25.82	31.77	42.74
C2	28.89	19.92	31.20	42.53	36.10	45.08	65.79	12.56	16.16	27.95	35.55
C3	33.89	17.42	34.15	60.55	55.23	63.15	85.18	31.82	35.49	39.01	51.58
C4	41.02	24.30	40.68	69.61	64.23	72.22	94.03	40.76	44.17	44.48	58.51
C5	40.68	24.30	41.02	65.12	58.87	67.70	88.14	35.34	38.16	37.06	51.25
C6	51.85	35.15	51.72	77.41	70.81	79.98	99.56	47.36	49.71	44.04	59.85

C7	58.33	41.68	57.74	86.18	79.88	88.77	108.79	56.38	58.89	52.73	68.83
C8	65.31	48.60	64.89	91.30	84.33	93.86	112.49	61.04	63.00	53.83	70.51
C9	52.17	38.48	53.73	63.68	54.58	66.00	80.27	33.70	33.31	19.94	36.51
C10	89.63	73.10	88.78	116.98	109.84	119.53	137.48	86.66	88.40	76.63	93.66
C11	79.62	63.66	78.32	110.61	104.67	113.21	133.68	81.14	83.78	76.20	92.81
C12	53.18	39.87	51.00	90.17	87.07	92.77	117.62	64.56	68.94	71.51	85.39
C13	—	16.72	3.70	41.01	42.67	43.37	71.96	29.87	35.63	56.26	59.72
C14	16.72	—	16.73	50.34	48.16	52.93	78.79	27.86	33.36	47.31	55.27
C15	3.70	16.73	—	44.54	46.37	46.87	75.59	33.13	38.94	58.88	62.96
C16	41.01	50.34	44.54	—	11.68	2.62	31.57	30.58	30.44	53.53	44.39
C17	42.67	48.16	46.37	11.68	—	13.06	30.66	23.54	21.54	42.61	32.71
C18	43.37	52.93	46.87	2.62	13.06	—	29.66	33.05	32.72	55.41	45.67
C19	71.96	78.79	75.59	31.57	30.66	29.66	—	53.39	49.99	63.71	48.01
C20	29.87	27.86	33.13	30.58	23.54	33.05	53.39	—	5.86	28.91	29.85
C21	35.63	33.36	38.94	30.44	21.54	32.72	49.99	5.86	—	25.12	24.13
C22	56.26	47.31	58.88	53.53	42.61	55.41	63.71	28.91	25.12	—	17.06
C23	59.72	55.27	62.96	44.39	32.71	45.67	48.01	29.85	24.13	17.06	—

Note. Computed via the Haversine formula ($R = 6,371$ km) from GPS-validated coordinates. — denotes the zero diagonal.