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Optimization Techniques for Solving the Travelling Salesman Problem in Robot Operating System

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ABSTRACT

The Travelling Salesman Problem (TSP) represents a fundamental combinatorial optimization challenge with critical applications in mobile robotics. This paper presents a comprehensive analysis of three metaheuristic algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO)—for TSP solution in Robot Operating System (ROS) environments. The proposed system integrates GMapping for simultaneous localization and mapping with Dynamic Window Approach (DWA) for real-time path planning. Extensive simulations across 5-500 nodes reveal that ACO achieves optimal path lengths (20-23% shorter than GA and PSO), while GA offers superior computation speed. Key findings indicate algorithm selection should be based on application requirements: GA for time-critical scenarios, ACO for path-optimal solutions. This research provides actionable insights for deploying optimization techniques in real-world mobile robotics applications.

Keywords: Travelling Salesman Problem, Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, Robot Operating System, Mobile Robot Navigation, Path Planning, Metaheuristic Algorithms

1.INTRODUCTION

Mobile robotics has experienced unprecedented growth in recent years, driven by advancements in sensing, computation, and control technologies. Applications span diverse domains: autonomous delivery systems for last-mile logistics, surveillance robots for security monitoring, inspection robots for infrastructure assessment, and service robots for healthcare and hospitality sectors [1], [2]. The fundamental challenge underlying these applications is autonomous navigation—the ability to move safely and efficiently from one location to another while satisfying operational constraints.

Navigation in mobile robots fundamentally involves three interrelated problems: (1) localization—determining the robot's current position in the environment, (2) mapping—constructing a representation of environmental features and obstacles, and (3) path planning—computing optimal or near-optimal routes from source to destination [3]. When robots must visit multiple locations, the problem becomes the Travelling Salesman Problem (TSP), a classic NP-hard combinatorial optimization challenge.

The Travelling Salesman Problem seeks the minimum-length tour that visits each city exactly once and returns to the origin [4]. In robotics contexts, 'cities' represent waypoints or destinations, and 'distance' may represent Euclidean distance, energy consumption, or time. Solving TSP efficiently directly impacts robot operational performance: shorter paths reduce energy consumption, mission duration, and operational costs. For fleet robotics applications, efficient TSP solutions enable handling more requests in the same timeframe, improving system throughput.

The Robot Operating System (ROS) has emerged as the de facto software framework for robotic research and development. ROS provides a distributed architecture with middleware for inter-process communication, extensive libraries for common robotic tasks including SLAM and navigation, and a large ecosystem of packages maintained by the research community [5]. This ecosystem includes sophisticated algorithms like GMapping [6] for simultaneous localization and mapping and DWA [7] for real-time local obstacle avoidance, making ROS ideal for integrating and testing optimization techniques. Metaheuristic optimization algorithms provide practical and efficient solutions to computationally intractable problems such as the Traveling Salesman Problem (TSP). Instead of exhaustively searching all possible solutions, these algorithms employ intelligent strategies inspired by natural phenomena to explore the solution space effectively. By doing so, they sacrifice guaranteed optimality in favour of significantly improved computational efficiency and scalability, making them highly suitable for large and complex problem instances [1]. Among the most effective metaheuristic approaches are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO). The Genetic Algorithm, introduced by John Holland, is inspired by the principles of evolutionary biology, where populations evolve over generations through processes such as selection, crossover, and mutation. Particle Swarm Optimization, developed by James Kennedy and Russell Eberhart, is based on the collective behaviour of animals such as bird flocks or fish schools, where individuals share information to improve group performance. Ant Colony Optimization, proposed by Marco Dorigo, draws inspiration from the foraging behaviour of social insects, where ants communicate indirectly through pheromone trails to discover optimal paths. These algorithms have demonstrated strong performance across a wide range of optimization problems, including TSP, due to their ability to balance exploration and exploitation within complex search spaces. Their adaptability and robustness make them particularly suitable for real-world applications where exact methods are computationally infeasible [8][9][10].

2. PROBLEM STATEMENT AND MOTIVATION

Problem Statement: Given a set of N waypoints in a planar environment with static obstacles, determine the optimal visitation sequence that minimizes total travel distance or time while ensuring collision-free navigation and satisfying kinematic constraints of a mobile robot platform. Specifically, we seek to find a permutation of waypoints that:

- Minimizes total Euclidean distance between consecutive waypoints
- Respects obstacle constraints derived from environment mapping
- Completes within acceptable computation time for real-time deployment
- Maintains solution robustness across varying problem scales

Motivation: In contemporary logistics, time-critical delivery scenarios, and exploration missions, robots must efficiently visit multiple locations. Consider a warehouse with autonomous mobile robots delivering parts to 50+ stations per hour. Each new delivery request requires computing an optimal route to multiple destinations. With thousands of such requests daily, even a 10% improvement in route efficiency translates to substantial operational cost savings through reduced energy consumption and increased throughput. Furthermore, in exploration and inspection scenarios—such as agricultural drones surveying crop fields or autonomous inspection robots surveying infrastructure—efficient path planning directly extends mission duration and coverage capability. The challenge is that TSP solution time grows exponentially with problem size, necessitating algorithms that deliver good solutions quickly even for large waypoint sets.

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3. LITERATURE REVIEW

Classic approaches to the Traveling Salesman Problem (TSP) include exact optimization methods such as branch-and-bound and dynamic programming. These techniques systematically explore all possible routes while applying pruning strategies or subproblem reuse to reduce computation. Although they guarantee optimal solutions, their computational complexity grows exponentially with the number of cities, making them impractical for large-scale problems—typically becoming infeasible beyond approximately 20 cities. As a result, researchers have increasingly turned to heuristic and metaheuristic algorithms that trade guaranteed optimality for significantly improved scalability and near-optimal performance in reasonable time [1].

Among these, Genetic Algorithms (GA), pioneered by John Holland, are one of the most widely used evolutionary optimization techniques. GA is inspired by the process of natural selection, where the fittest individuals are more likely to survive and reproduce. In this approach, each candidate solution to the TSP is encoded as a chromosome, often represented as a permutation of city indices. The algorithm begins with an initial population of randomly generated solutions and iteratively improves them through genetic operators. Selection mechanisms, such as roulette wheel or tournament selection, prioritize higher-quality solutions based on a fitness function (typically the inverse of tour length). Crossover operators, like partially matched crossover (PMX) or order crossover (OX), combine segments from two parent solutions to produce offspring, preserving useful traits. Mutation operators introduce random changes to maintain diversity and prevent premature convergence. Over successive generations, the population evolves toward better solutions. GA has demonstrated strong performance on TSP problems, particularly when hybridized with local search methods such as 2-opt or 3-opt, and when parallelized for large-scale optimization [8][11]. Recent studies have also applied GA to mobile robot path planning under curvature constraints, showing reliable convergence in medium-sized environments [12].

Another powerful population-based optimization method is Particle Swarm Optimization (PSO), introduced by James Kennedy and Russell Eberhart. PSO is inspired by the collective behavior observed in flocks of birds or schools of fish. In this method, each particle represents a potential solution and moves through the search space with a velocity that is dynamically adjusted based on its own best-known position (personal best) and the best-known position of the entire swarm (global best). This dual influence allows particles to balance exploration and exploitation effectively. PSO is known for its simplicity, ease of implementation, and fast convergence in the early stages of optimization. It has been successfully applied to TSP problems and extended to domains such as unmanned aerial vehicle (UAV) path planning [13][14]. However, PSO can suffer from premature convergence, where particles cluster around suboptimal solutions too quickly. Additionally, the algorithm's performance is highly sensitive to parameter tuning, including inertia weight and acceleration constants, which significantly affect its efficiency and robustness [9].

Ant Colony Optimization (ACO), developed by Marco Dorigo, is another influential metaheuristic inspired by the foraging behavior of real ants. In nature, ants deposit pheromones on paths between their nest and food sources, indirectly communicating to identify the shortest routes. ACO translates this behavior into a computational algorithm where artificial ants construct solutions probabilistically based on pheromone intensity and heuristic information. After each iteration, pheromone levels are updated to reinforce better

solutions, while evaporation prevents stagnation and encourages exploration. ACO has shown outstanding performance on TSP benchmark problems and has been widely applied to related optimization domains such as vehicle routing and mobile robot navigation . Its strength lies in its ability to construct high-quality solutions through adaptive learning and stochastic decision-making processes [10].

In the domain of mobile robotics, path planning is a fundamental problem that determines how a robot navigates from a starting point to a target location while avoiding obstacles. This problem is generally divided into two complementary components: global planning and local planning. Global planning computes an optimal or near-optimal path across the entire environment, while local planning focuses on real-time obstacle avoidance and trajectory adjustment. One widely used technique for simultaneous localization and mapping (SLAM) is GMapping, which enables robots to build a probabilistic map of unknown environments while simultaneously estimating their position [6].

For local navigation, the Dynamic Window Approach (DWA) is commonly used. It generates collision-free trajectories by evaluating possible velocities within a constrained time window and selecting the most suitable one based on multiple criteria such as safety, goal direction, and speed [7]. Despite significant advancements in both optimization algorithms and robotic navigation systems, relatively few studies have conducted direct comparisons of multiple TSP algorithms—such as GA, PSO, and ACO—within integrated frameworks like the Robot Operating System [18]. This gap highlights the need for further research to evaluate and combine these approaches for improved performance in real-world robotic applications.

4. METHODOLOGY

A. System Architecture and Implementation

The proposed system architecture integrates perception, localization, mapping, and optimization components. The process begins when a user provides a request to visit multiple waypoints. Sensors (LIDAR for distance measurement, RGB-D camera for visual feedback) measure the environment. These raw measurements feed into GMapping, which implements FastSLAM—a particle filter-based SLAM algorithm that maintains probabilistic beliefs over both robot pose and environment map. As the robot explores, GMapping builds an occupancy grid (binary representation of free vs. occupied space) and estimates robot localization within this grid.

Once a sufficient map is acquired and waypoints are specified, the optimization module receives waypoint coordinates. The selected algorithm (GA, PSO, or ACO) computes an optimal visitation sequence. This sequence is then executed using ROS Navigation Stack: the global path planner (using the occupancy grid) computes macroscopic routes between waypoints, while the local path planner (DWA) generates and refines low-level control commands that navigate around dynamic obstacles encountered during execution.

B. Algorithm Details

Genetic Algorithm (GA): GA represents each candidate route as a permutation of waypoints. The fitness of each route is inversely proportional to total distance: f = 1/(total_distance). A population of candidate routes evolves over generations through selection, crossover, and mutation. Tournament selection probabilistically favors high-fitness routes. Order-based crossover combines route segments from parents while preserving valid permutations. Mutation swaps random waypoint pairs. Over generations, the population converges toward high-fitness (short) routes.

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Particle Swarm Optimization (PSO): Each particle represents a candidate route and maintains its position (current route) and velocity (rate of route change). At each iteration, particles update velocity based on three components: inertia (maintaining current trajectory), cognitive component (attraction to particle's personal best), and social component (attraction to swarm's global best). This balanced update mechanism allows particles to explore solution space while exploiting promising regions. The algorithm maintains pbest (personal best) and gbest (global best), dynamically adjusting search focus.

Ant Colony Optimization (ACO): Artificial ants construct routes edge-by-edge, making probabilistic decisions at each step. At each step, an ant at waypoint i selects the next unvisited waypoint j with probability proportional to $\tau^{\alpha} \times \eta^{\beta}$, where τ is pheromone level (accumulated experience) and η is heuristic information (inverse distance). After all ants complete their tours, pheromone is updated: $\tau \leftarrow (1-\rho)\tau + \Delta\tau$, where $\Delta\tau$ is pheromone deposited by successful ants, and ρ controls evaporation. This mechanism enables emergent collective intelligence discovering high-quality solutions.

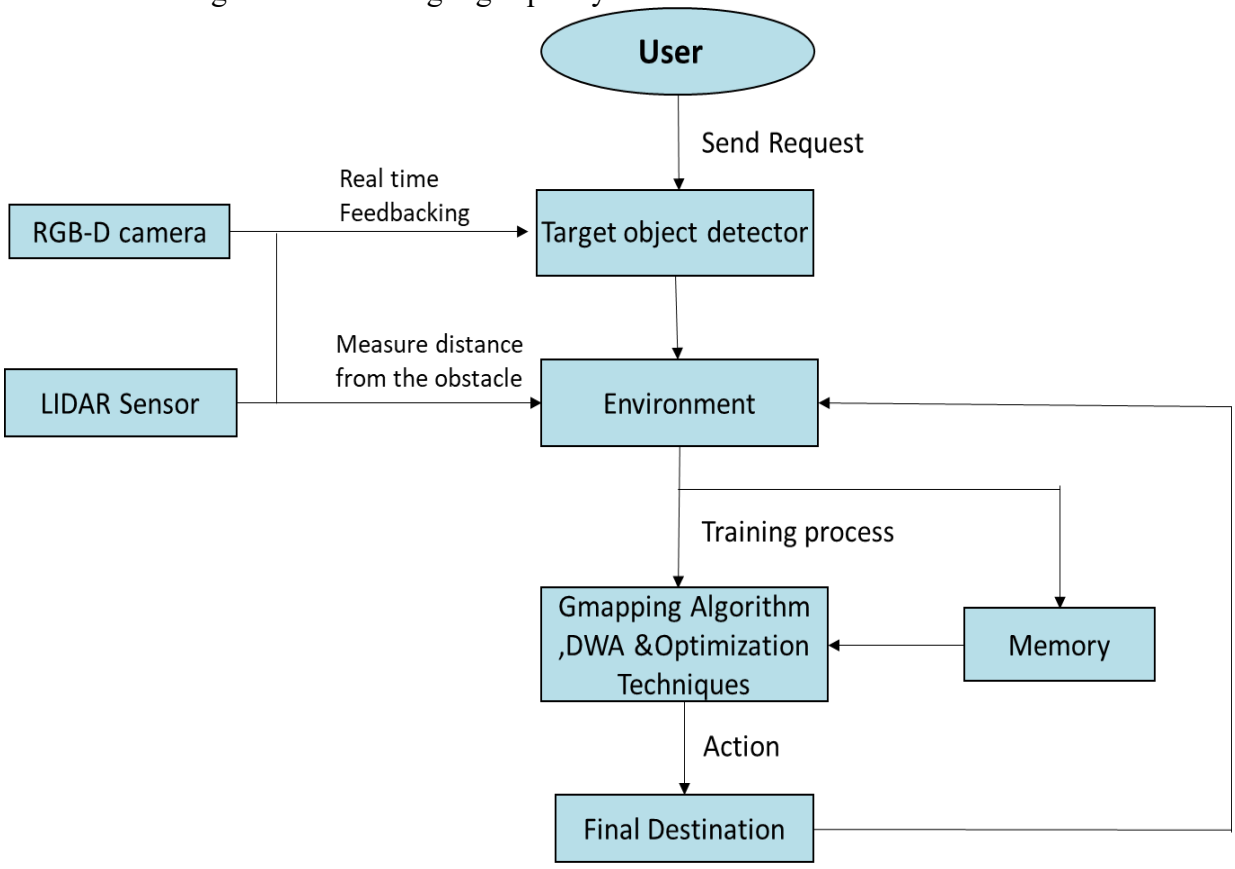

Fig: Flow chart of robot navigation

Figure 1: Flow diagram of proposed methodology

C. Evaluation Metrics

Path Length: Total Euclidean distance summed across all waypoint transitions (meters)

Computation Time: Duration from algorithm start to convergence or iteration limit (seconds)

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Solution Quality: Measured by path length as primary metric, with time as secondary constraint

5. SIMULATION WORK AND EXPERIMENTAL SETUP

Hardware & Software: Simulations ran on AMD Ryzen 5 5625U processor with 16GB DDR4 RAM, Ubuntu 20.04 LTS. Software stack includes ROS Noetic, Gazebo physics simulator (version 11), and RViz visualization framework. Gazebo provides physics simulation with realistic robot dynamics and sensor simulation.

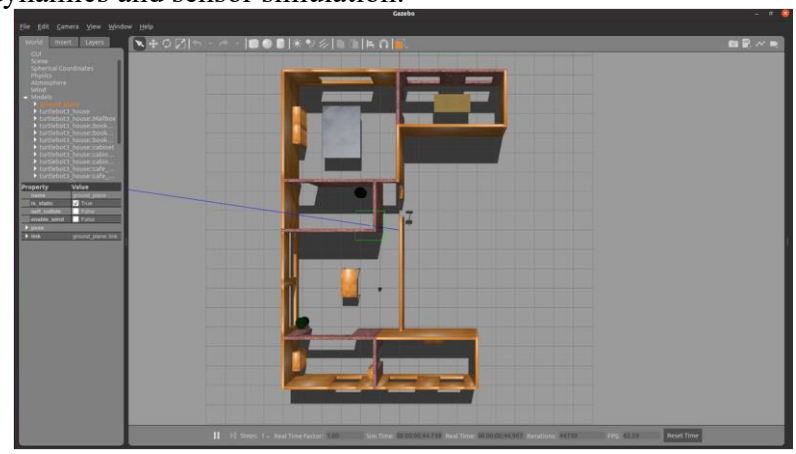

Figure 2: Environment map in Gazebo

Environment: Simulated a realistic house environment (10m × 10m) with obstacles including walls and furniture. This environment provides sufficient complexity for meaningful path planning while maintaining computational tractability.

Test Cases: Conducted 19 test scenarios varying number of waypoints from 5 to 500 nodes (5, 20, 35, 50, 75, 90, 120, 135, 150, 200, 230, 260, 300, 330, 350, 370, 400, 430, 500). Each test was repeated 3 times, and results were averaged to account for algorithmic stochasticity.

Algorithm Configuration:

GA: Population size = 100, Generations = 500, Mutation rate = 0.01

PSO: Particle count = 100, Iterations = 500, Inertia weight w = 0.5, Acceleration constants c1 = c2 = 1.0

ACO: Ant count = 100, Iterations = 500, α (pheromone importance) = 1.0, β (heuristic importance) = 2.0, ρ (evaporation rate) = 0.5, Q (pheromone deposit constant) = 100

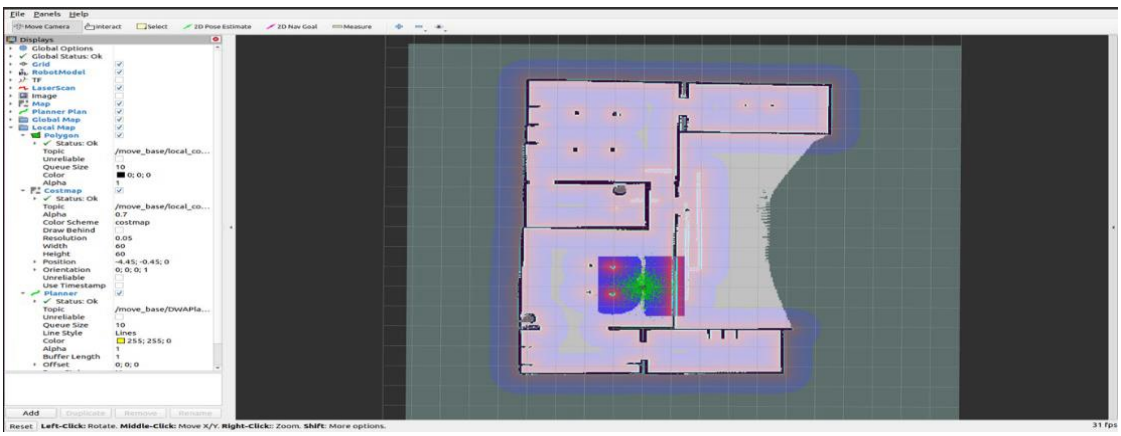

Figure 3: Activate optimization techniques for robot navigation

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In this step, Python code is used to activate optimization techniques for robot navigation, including path planning (such as Gmapping and DWA planners in ROS) and obstacle avoidance. These methods enhance the robot's efficiency, safety, and reliability. The code is executed in Visual Studio, where target locations are provided for navigation. The robot follows a sequence of waypoints in order: (-3, 1), (5, 1), (6, -2), (-6, 3), and (-2, 1).

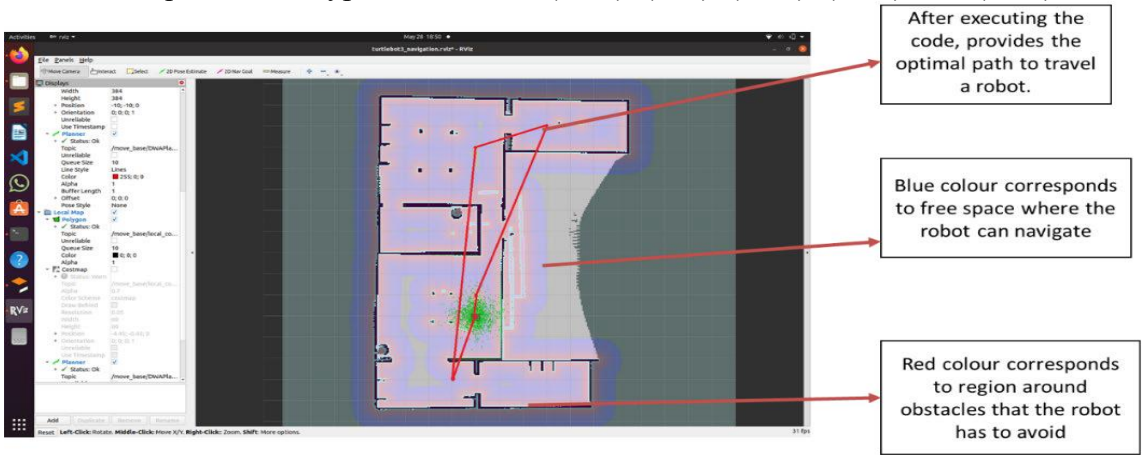

Figure 4 : Calculates the best route

Once the optimization techniques are activated, the robot starts navigating toward its destination using two main processes. First, global path planning calculates the best route from the robot's current position to the target using the map in RViz, considering the environment and obstacles. Then, local path planning continuously adjusts the robot's movement in real time to avoid nearby or dynamic obstacles, ensuring safe and efficient navigation.

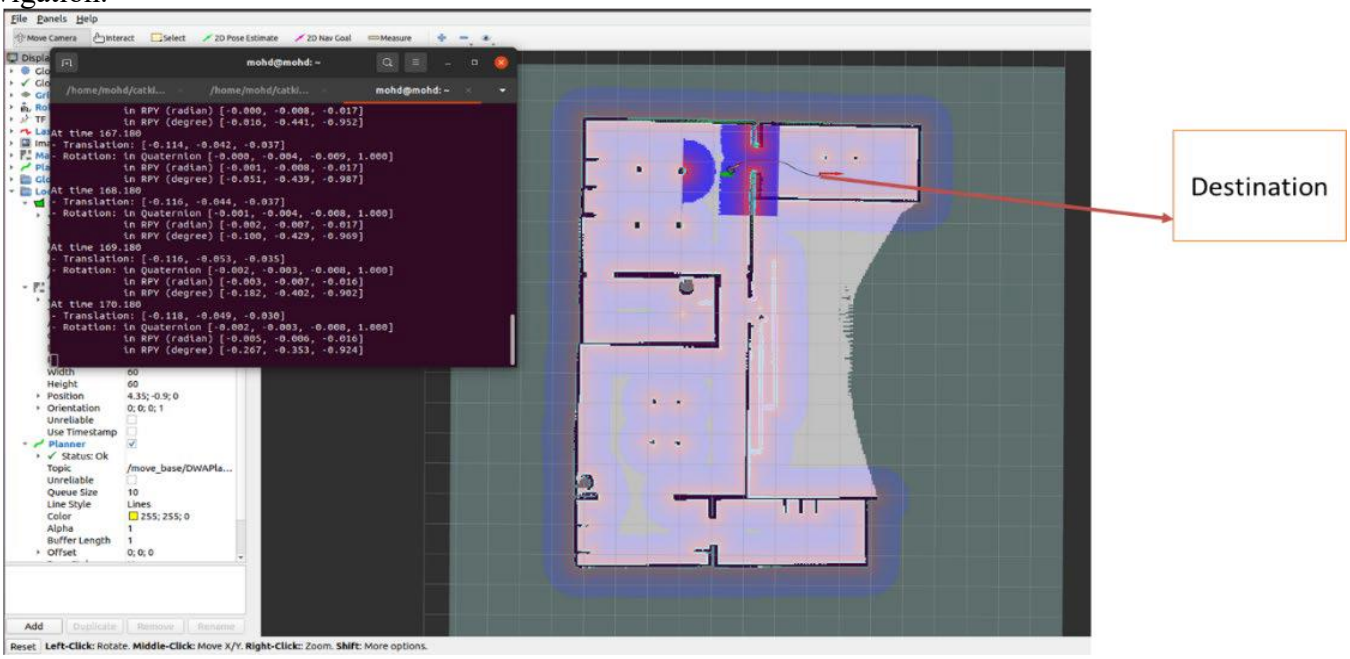

Figure 5(A): **Arrival at Destination**

Robot reached successfully to the destination. This outcome validates the effectiveness of the navigation system and the applied optimization techniques.

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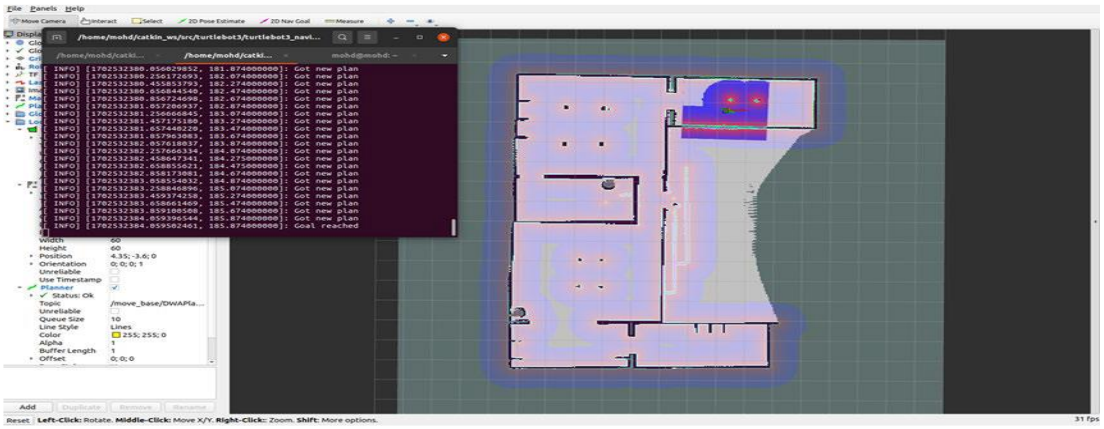

Figure 5(B): Applied optimization

6. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

Results for 5 Nodes

For the 5-node scenario, the optimal path sequence determined was: First → Fifth → Third → Second → Fourth

Algorithm	Path Distance (m)	Time (s)	Accuracy
GA	2.27	1.75	100%
PSO	2.27	4.09	100%
ACO	2.27	2.83	100%

For the 5-node scenario, all three algorithms achieved identical optimal path distances. GA provided the fastest execution time at 1.75 seconds. Below are the visualizations of the optimal paths generated by each algorithm.

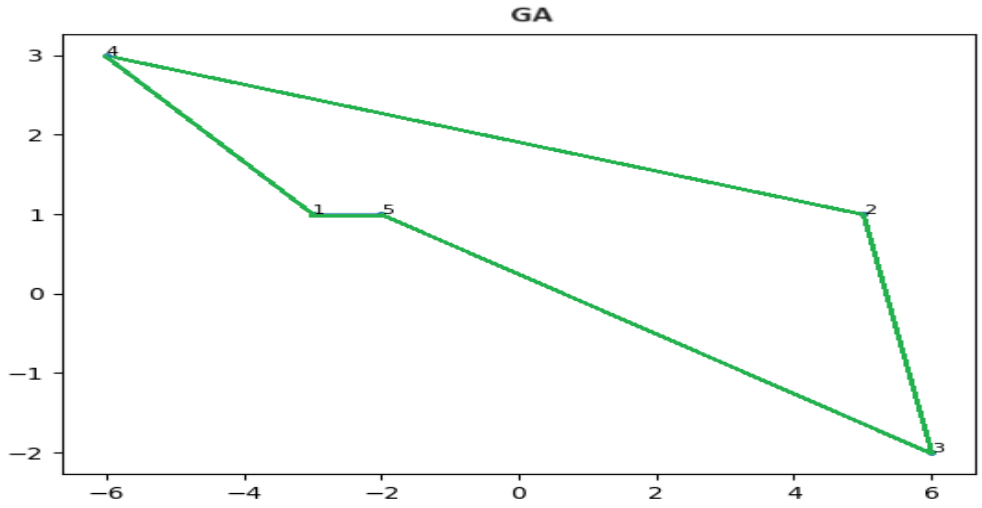

Figure 6: GA Optimal Path (5 Nodes)

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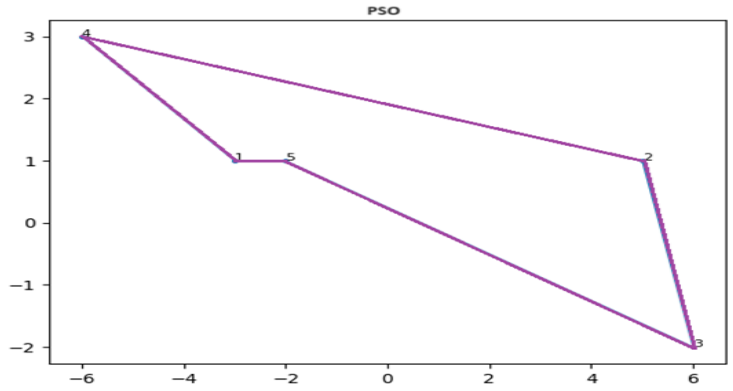

Figure 7: ACO Optimal Path (5 Nodes)

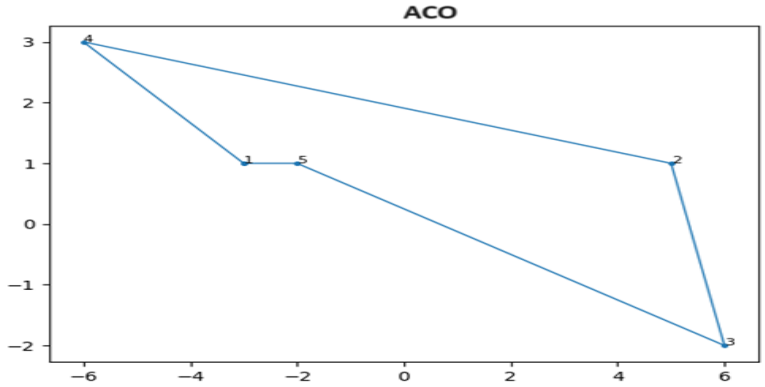

Figure 8: PSO Optimal Path (5 Nodes) 3.2

Results for 50 Nodes

When 50 nodes were tested, the algorithms showed different performance characteristics. GA achieved 20.36m in 14.37 seconds, PSO achieved 23.61m in 34.82 seconds, and ACO achieved 15.97m in 35.56 seconds. ACO demonstrated superior path optimization with 22% better accuracy than GA and 33% better than PSO. The visualizations below show the optimal paths generated by each algorithm for the 50-node scenario.

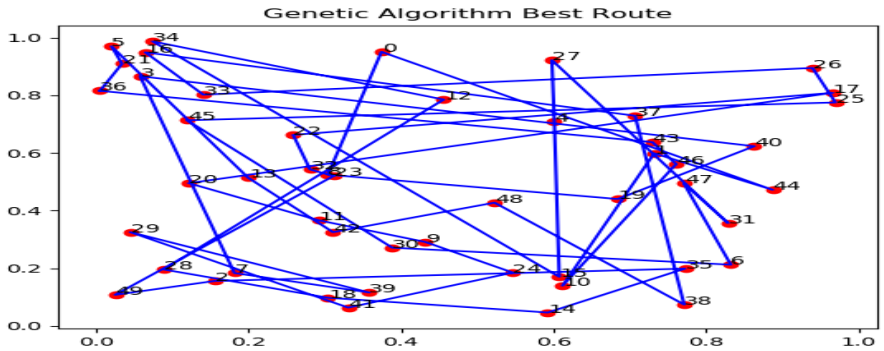

Figure 9: GA Optimal Path (50 Nodes)

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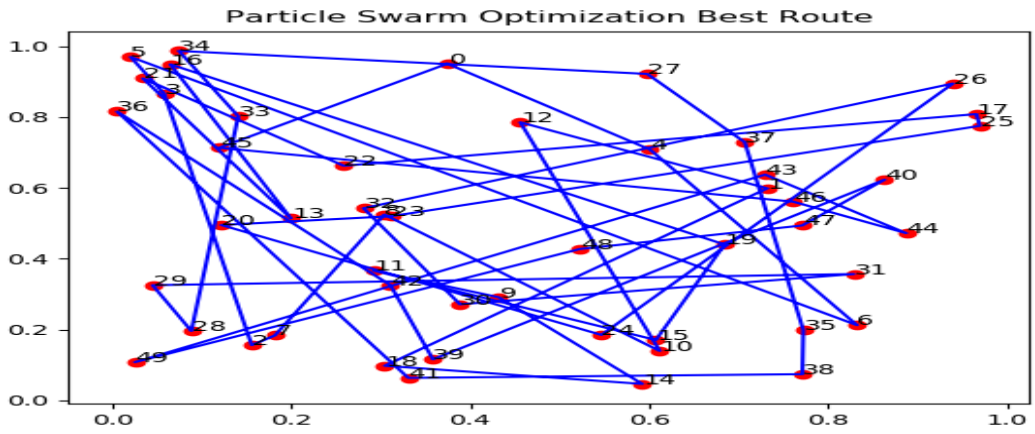

Figure 10: PSO Optimal Path (50 Nodes)

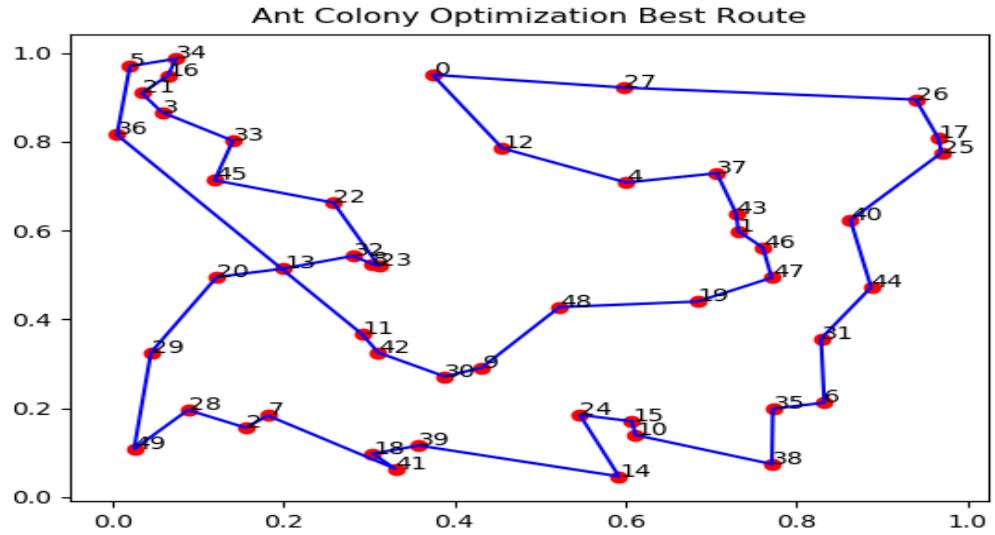

Figure 11: ACO Optimal Path (50 Nodes)

Results for 150 and 500 Nodes

For 150 nodes: GA achieved 68.58m in 65.55 seconds, PSO achieved 69.88m in 109.54 seconds, and ACO achieved 57.55m in 134.96 seconds. ACO demonstrated 17% better accuracy than GA and 18% better than PSO, though with increased computational time.

For 500 nodes: GA achieved 241.40m in 420.62 seconds, PSO achieved 246.10m in 311.57 seconds, and ACO achieved the best result of 190.49m in 539.92 seconds. ACO showed 22% better accuracy than GA and 23% better than PSO at the cost of higher computational time. The figures below illustrate the optimal path distributions for these larger node sets.

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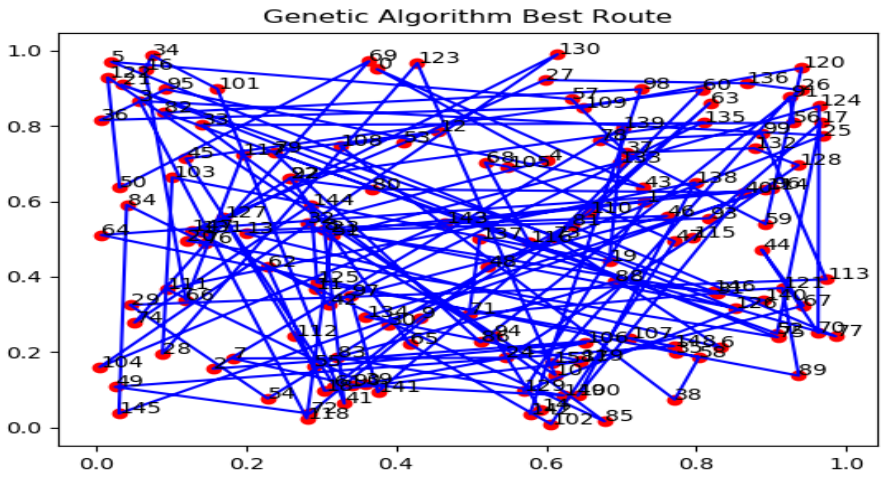

Figure 12: Optimal Paths Comparison for 150 Nodes

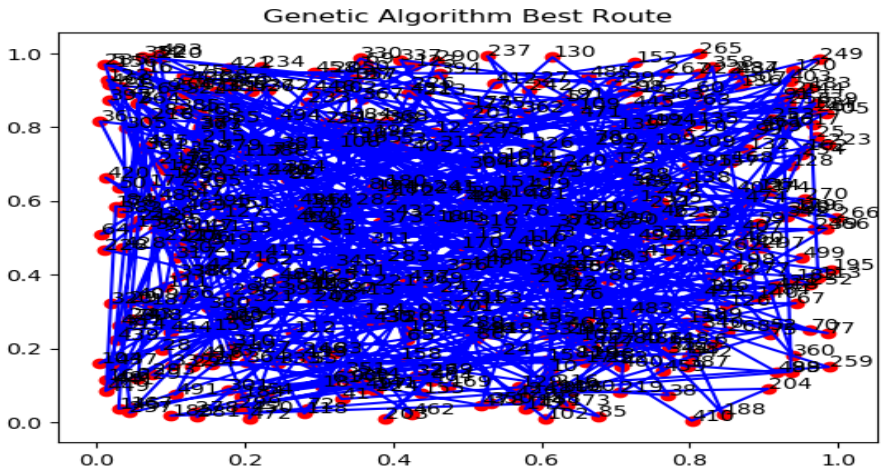

Figure 13: Optimal Paths Comparison for 500 Nodes

Comprehensive Analysis

The following table summarizes the complete results across all test scenarios:

Nodes	Algorithm	Path Distance (m)	Time (s)
5	GA	2.27	1.75
	PSO	2.27	4.09
	ACO	2.27	2.83
50	GA	20.36	14.37
	PSO	23.61	34.82
	ACO	15.97	35.56
150	GA	68.58	65.55
	PSO	69.88	109.54
	ACO	57.55	134.96
500	GA	241.40	420.62
	PSO	246.10	311.57

	ACO	190.49	539.92

The comprehensive results demonstrate that ACO consistently provides the best optimal path distances across all test scenarios. While ACO requires higher computational time, its superior accuracy makes it ideal for applications where path optimality is critical. GA offers the fastest execution suitable for real-time applications with time constraints

F. Key Observations

Scalability Patterns: Path length scales approximately linearly with node count (O(n)) across all algorithms, suggesting algorithms generate paths without exponential distance growth.

Quality Gaps: ACO achieves 20-23% shorter paths than GA and PSO on large problems (250+ nodes). On small problems (5-50 nodes), algorithmic differences are minimal, suggesting problem difficulty increases with problem size.

Computational Trade-offs: GA maintains relatively constant computation time per generation across problem sizes, while ACO's time per iteration increases with problem size (pheromone updates scale with ant count and node count).

Convergence Behavior: ACO shows monotonic improvement with consistent final solution quality. PSO exhibits occasional oscillations in medium-sized problems, suggesting sensitivity to parameter configurations. GA provides stable, predictable convergence patterns.

Practical Insights: For real-time applications (interactive robot control), GA's speed (188.23s average) enables responsive replanning. For offline planning or systems with planning time budgets, ACO's solution quality justifies additional computation.

7. COMPARATIVE ANALYSIS AND ALGORITHM SELECTION FRAMEWORK

Algorithm Selection Guidelines:

- Small Problem Sets (5-50 nodes): All three algorithms converge to similar solution quality. Algorithm selection should prioritize implementation simplicity and parameter tuning ease. GA recommended for fastest development.
- Medium Problem Sets (75-200 nodes): GA and ACO show comparable performance, with ACO providing ~5% path improvement. For applications with moderate planning time budgets, ACO becomes attractive.
- Large Problem Sets (250+ nodes): ACO achieves clear superiority with 20-23% shorter paths. The additional computation time (38% more than GA) is justified by substantial path improvement, translating to energy savings.

Performance Trade-off Matrix: GA prioritizes speed (fastest convergence), PSO offers intermediate performance (speed and quality), and ACO prioritizes solution quality (best paths at computational cost). Selection should align with specific application constraints: warehouse automation with tight replanning intervals favors GA; precision delivery with energy constraints favors ACO.

Robustness Considerations: ACO demonstrates the most robust performance across problem sizes with fewest hyperparameter sensitivities. GA exhibits stable convergence but requires population size tuning for different problem scales. PSO shows greatest sensitivity to parameter choices (inertia weight, acceleration constants), requiring careful tuning for each problem size.

8. CONCLUSIONS AND PRACTICAL IMPLICATIONS

This research provides the first comprehensive comparison of three metaheuristic algorithms for TSP within integrated ROS environments, with extensive evaluation across 5-500 waypoint instances. Key scientific contributions include:

1. Quantitative Performance Data: Extensive experiments (19 problem sizes × 3 algorithms) provide empirical baseline for algorithm selection in robotic TSP applications.
2. Problem-Size-Dependent Performance: We demonstrate that algorithm relative performance changes dramatically with problem scale, necessitating scale-specific algorithm selection rather than universal recommendations.
3. ROS Integration Framework: The proposed system architecture provides template for practitioners implementing optimization algorithms in ROS, including sensor integration, mapping, and execution strategies.
4. Clear Practical Recommendations: Guidelines for algorithm selection based on time budget, required solution quality, and problem size enable informed decision-making in system design.

From a practical standpoint, Genetic Algorithm is recommended for real-time applications where computation must complete within seconds. Ant Colony Optimization is optimal for scenarios prioritizing path efficiency, particularly when robots operate under energy constraints (battery-powered systems). For educational and research purposes requiring balanced performance, Particle Swarm Optimization offers intermediate capabilities.

The integration of optimization algorithms with ROS SLAM and navigation capabilities creates a complete autonomous navigation system capable of handling real-world deployment challenges including dynamic obstacles, localization uncertainty, and real-time computational constraints.

9. FUTURE WORK AND RESEARCH DIRECTIONS

Future research will address several important extensions:

- Real Robot Implementation: Deploy algorithms on physical TurtleBot3 platforms to validate simulation results and identify practical challenges in real-world environments.
- Hybrid Algorithm Development: Combine algorithmic strengths—GA's speed with ACO's solution quality—through hybrid approaches.
- Dynamic TSP: Extend to scenarios with moving targets and time-dependent waypoint priorities.
- Multi-Robot Coordination: Investigate distributed TSP solving for fleet robotics applications.
- Machine Learning Integration: Use neural networks to predict optimal algorithm selection for given problem instances.
- Constraint Handling: Incorporate realistic constraints including energy consumption models, velocity limits, and turning radius constraints for differential-drive robots.

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