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A hybrid graph–grid improved ant colony optimization framework for accurate and low-latency path planning

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ABSTRACT

Efficient path planning is essential for safe autonomous vehicle navigation. However, conventional ant colony optimization (ACO) often suffers from premature convergence, local optima, and high computational costs. This study aims to improve path planning accuracy and computational efficiency by integrating graph- and grid-based representations into an enhanced ACO algorithm. The proposed method was evaluated on 30 navigation routes at Universitas Sriwijaya (UNSRI), Indralaya, under obstacle-free and obstacle scenarios. Experimental results showed that the proposed algorithm outperformed conventional ACO in route accuracy and computational efficiency. In obstacle-free scenarios, the mean absolute error (MAE) decreased from 70.7 m to 2.8 m. The average path generation time was 0.47 s for obstacle-free routes and 0.21 s for routes with obstacles. These findings demonstrate that integrating graph and grid based representations improves path planning accuracy and reduces computational time, offering an effective approach for real time autonomous vehicle navigation.

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1. INTRODUCTION

Autonomous vehicles have emerged as one of the most promising technologies for intelligent transportation systems because of their potential to improve traffic safety, transportation efficiency, and driving comfort. To navigate autonomously from a starting point to a destination, autonomous vehicles require a reliable navigation system capable of generating safe, efficient, and collision-free routes. Among the core components of autonomous navigation, path planning plays a crucial role in determining the optimal route while minimizing travel distance, computational cost, and execution time. Consequently, the development of efficient path planning algorithms has become an active research topic in autonomous driving and mobile robotics.

Among various optimization techniques, ant colony optimization (ACO) has attracted considerable attention owing to its distributed search mechanism and strong optimization capability. Inspired by the foraging behavior of ants, ACO has demonstrated remarkable effectiveness in solving complex combinatorial optimization problems [1]. Previous studies have shown that ACO provides several advantages for autonomous vehicle path planning, including high reliability in autonomous navigation [2], [3], superior optimization performance with fewer iterations than particle swarm optimization (PSO) under specific

conditions [4], algorithmic simplicity [5], ease of implementation [6]-[8] and robust performance in solving shortest path optimization problems [9], [10]. These characteristics have established ACO as one of the most widely adopted metaheuristic algorithms for autonomous vehicle path planning.

Despite these advantages, conventional ACO still suffers from several inherent limitations that restrict its performance in practical autonomous navigation scenarios. As pheromone accumulates over successive iterations, the search process tends to converge prematurely toward locally optimal solutions, reducing the algorithm's exploration capability [1]. Furthermore, in complex environments containing multiple alternative routes or obstacles, conventional ACO is prone to deadlock conditions and requires additional computational effort to escape local optima, leading to longer execution times and reduced path quality [1]. These limitations have motivated researchers to develop various improvement strategies to enhance the search capability, convergence speed, and computational efficiency of the ACO algorithm.

To overcome these limitations, numerous studies have proposed hybrid optimization approaches by combining ACO with other intelligent algorithms. Hybrid path-planning approaches integrate two or more algorithms to exploit their complementary strengths. Previous studies have combined ACO with algorithms such as artificial potential field (APF), genetic algorithm (GA), and PSO to improve convergence speed and solution quality.

One of the earliest approaches integrates ACO with fuzzy control to dynamically adjust pheromone and heuristic parameters, thereby improving convergence speed and strengthening the global search capability [8]. Similarly, GA have been incorporated into ACO to improve exploration ability through adaptive crossover, mutation, elite retention, and deletion strategies, resulting in significant reductions in iterations and turning points while producing smoother paths [3]. In addition, PSO has been combined with ACO to initialize pheromone distribution and improve the state transition mechanism, enabling faster convergence and higher search efficiency than conventional ACO and PSO algorithms [9]. Numerous other hybrid strategies have also been reported, confirming that combining ACO with complementary optimization techniques can improve solution quality and convergence behavior [10]–[17].

Another research direction focuses on improving the internal mechanisms of ACO, including pheromone updating strategies, heuristic functions, adaptive parameter adjustment, and exploration mechanisms. These improvements primarily aim to reduce premature convergence while maintaining computational efficiency. Techniques such as enhanced heuristic distance calculation, pheromone diffusion models, backtracking strategies, and path merging have been proposed to accelerate convergence and improve path optimality, particularly in large and complex environments [18]. Parallel ACO has also been introduced to improve the efficiency of automated guided vehicles (AGVs) through multi-subcolony cooperation and multi-objective optimization based on travel distance and turning cost, resulting in improved stability and convergence speed [19].

Further improvements include path smoothing strategies, directional guidance, and adaptive optimization mechanisms. For instance, an improved ant colony optimization (IACO) incorporating path straightening factors and the max–min ant system (MMAS) reduces unnecessary turning angles and avoids premature convergence by limiting pheromone concentration [2]. Moreover, analytic hierarchy process (AHP)-based weighting strategies and dynamic optimization techniques have been integrated to simultaneously consider path length, travel time, and traffic conditions, leading to reduced travel time and improved convergence performance compared to conventional ACO [20]. Additional enhancements reported in [6], [21]–[27], further demonstrate improvements in path quality, computational efficiency, and algorithm stability.

Although these studies have considerably IACO performance, several limitations remain. Hybrid ACO methods increase algorithmic complexity due to the integration of additional optimization techniques such as fuzzy logic, GA, and PSO, resulting in higher computational overhead and reduced suitability for real-time applications [3], [8], [9].

Meanwhile, most IACO approaches are designed primarily for grid-based environments [2], [18]–[24], limiting their ability to exploit the computational efficiency of graph-based representations. Graph-based and grid-based representations offer different advantages for autonomous path planning. A graph representation describes a road network through a limited number of nodes and edges, typically corresponding to intersections, turning points, and connected road segments. This compact representation substantially reduces the number of candidate states that need to be evaluated and is therefore advantageous in terms of computational efficiency. However, conventional graph-based ACO commonly incorporates distance-related heuristic information into the transition probability. This mechanism tends to favor geographically closer nodes and, under certain road configurations, may restrict the exploration of alternative routes and increase the risk of premature convergence.

Grid-based representations provide a different search behavior by dividing the environment into spatially distributed cells. The availability of multiple neighboring cells allows the search process to explore alternative spatial directions without relying exclusively on the direct distance to a destination or candidate

location. This characteristic can provide greater exploration flexibility, particularly when the environment contains complex road structures or local obstacles. However, the number of candidate cells increases with the size and resolution of the environment, which can considerably increase the computational burden of the path planning process.

These characteristics reveal a trade off between the computational efficiency of graph-based planning and the exploration flexibility associated with grid-based planning. Existing enhanced ACO methods have addressed path-planning limitations through modifications to pheromone updating, heuristic information, or additional optimization mechanisms. Nevertheless, the distance-driven selection mechanism in graph-based ACO remains an important factor that can influence the balance between exploration and exploitation. Modifying other components of ACO does not necessarily eliminate the bias introduced by distance when selecting the next graph node.

This study addresses this issue by modifying the node transition probability of graph based ACO. The proposed IACO assigns a zero value to the distance related component of the transition probability. Consequently, the selection of the next node is no longer directly biased toward geographically closer nodes, allowing the search process to explore alternative connected nodes more freely. Importantly, the proposed modification does not require probability calculations for every grid cell. The search is still performed over graph nodes representing relevant road locations, such as intersections and turning points. Therefore, the proposed approach retains the computational advantage of graph-based planning while introducing a grid-inspired exploration behavior. This design is intended to reduce premature convergence associated with distance-biased graph exploration without introducing the computational burden inherent in cell-by-cell grid-based search.

The main novelty of the proposed method lies in modifying the node-selection mechanism of graph-based ACO rather than constructing two independent search spaces. The proposed IACO retains the compact graph representation of the road network but removes the direct influence of the distance-related component from the transition probability by assigning this component a zero value. This modification changes the selection behavior of the graph-based search by reducing the preference for geographically closer nodes and thereby providing greater opportunity to explore alternative connected routes. The resulting behavior is inspired by the broader spatial exploration characteristic of grid-based search, while the actual probability calculation remains restricted to graph nodes.

Based on the identified research gaps, this study seeks to answer the following research question:

a. How does removing the distance-related component from the node-transition probability affect the exploration capability and path quality of graph-based ACO?
b. To what extent does the proposed IACO improve the balance between path-distance accuracy and computational efficiency compared with traditional ACO-based path planning?
c. How effectively can the proposed IACO adapt the planned path to road obstacles while maintaining low path-planning latency?

The contributions of this study can be summarized as follows. First, a graph-based representation is employed to model the road network using relevant locations, including intersections, turning points, and origin–destination nodes, thereby limiting the search space to feasible road connectivity. Second, an IACO strategy is introduced by eliminating the direct contribution of the distance-related term in the node-transition probability. This modification is designed to reduce distance-driven search bias and improve exploration without requiring probability calculations over individual grid cells. Third, the proposed IACO is evaluated against the conventional ACO-based approach under obstacle-free and obstacle-present conditions to examine route-distance deviation, route generation time, and route adaptation. The mobile application and associated software components are used as an experimental platform for implementing and evaluating the proposed method and are therefore considered supporting implementation components rather than the primary technical contribution.

2. METHOD

In conventional ACO, the probability of selecting the next node is determined by the pheromone intensity and heuristic information associated with the candidate transition. The distance-related heuristic generally provides a preference for shorter transitions, allowing ants to favor nodes that are geographically closer. Although this mechanism can guide the search toward shorter paths, excessive dependence on distance may reduce exploration when a locally attractive node does not lead to a globally favorable route.

2.1. Environmental representation

The road network of the study area was represented as a connected graph consisting of nodes and edges. Nodes were defined at locations that are relevant to route connectivity, including road intersections, significant turning points, and predefined origin and destination locations. An intersection was represented by a node when

two or more traversable road segments converged at the same location. Additional nodes were introduced at turning locations where a change in road direction was required to preserve the geometric characteristics of the road. The origin and destination coordinates were associated with the nearest feasible graph nodes.

An edge was established between two nodes when a continuous and traversable road segment connected the corresponding locations. The edge therefore represents the connectivity between two relevant road locations rather than an individual spatial cell. This representation substantially reduces the number of candidate locations considered during route generation compared with a cell-based grid representation. The resulting graph provides the search structure used by the proposed IACO, while the grid concept is incorporated at the algorithmic level through the modified node-selection mechanism rather than through cell-by-cell probability calculation.

2.2. Proposed grid–graph integration

In the proposed IACO, the distance-related component of the transition probability is assigned a zero value. Consequently, the direct contribution of distance to the node-selection probability is eliminated, while the pheromone information remains available to guide the search based on the collective experience accumulated during previous iterations. This modification allows candidate graph nodes to be selected without an explicit preference solely based on their geometric proximity.

The modification is intended to provide a grid-inspired exploration behavior within a graph-based search structure. In a grid environment, the search is not restricted to selecting a node solely because it provides the shortest immediate distance; instead, multiple spatially connected alternatives can be explored according to the search mechanism. The proposed IACO adopts a similar principle while maintaining the graph representation. Thus, the exploration behavior is modified without increasing the number of candidate states to the scale of individual grid cells.

2.3. Transition probability model

In the traditional ACO, the probability of an ant moving from node (i) to node (j) is defined as (1):

$$P^{K}{}_{ij}(\mathrm{t}) = \begin{cases} \dfrac{\tau^{a}{}_{ij}(t)\eta^{\beta}{}_{ij}(t)}{\sum_{s\epsilon allowed}\tau^{a}{}_{is}(t)\eta^{\beta}{}_{is}(t)}, s \in \mathrm{allowed}_{k} \\ 0, s \notin \mathrm{allowed}_{k} \end{cases} \quad (1)$$

where $\tau^{a}{}_{ij}(t)$ represents pheromone intensity and $\eta^{\beta}{}_{ij}(t)$ denotes heuristic information. The parameter alpha controls the influence of pheromone trails, while beta controls the influence of the heuristic distance. A high value of alpha reduces randomness in the search process, whereas an excessively high value of beta may lead the algorithm to premature convergence into local optima [12]. In grid-based environments, the distance component (d_{ij}) becomes uniform due to equal grid spacing, which reduces its discriminative effect. Conversely, in graph-based environments, heuristic evaluation is performed only at intersection nodes, reducing computational load but increasing the risk of local minima.

In this study, to further enhance exploration capability within the grid–graph framework, the parameter beta is set to zero, thereby eliminating the influence of distance-based heuristics and allowing pheromone information to dominate the decision-making process.

2.4. Computational efficiency improvement

Although the proposed method adopts a grid-inspired exploration principle, it does not perform the ACO probability calculation for every grid cell in the environment. The transition probability is evaluated only for graph nodes that represent relevant road locations. As a result, the number of candidate nodes remains substantially smaller than the number of cells required by a conventional grid-based representation.

This distinction is important because the proposed method does not attempt to reproduce the complete computational structure of grid-based ACO. Instead, it transfers the exploration principle of grid-based search to a graph-based node-selection mechanism. The resulting approach retains the reduced search space of the graph representation while reducing the direct influence of distance on node selection. Therefore, the proposed modification is expected to improve the exploration capability of graph-based ACO without introducing the computational overhead associated with evaluating a large number of grid cells.

3. RESULTS AND DISCUSSION

3.1. Experimental setup

The proposed method was evaluated using a real-world dataset consisting of latitude and longitude coordinates of road networks within the Universitas Sriwijaya (UNSRI) campus, Indralaya, Indonesia with

routes depicted as shown in Figure 1. The selected environment represents a suburban-scale scenario commonly encountered in autonomous vehicle applications, where road connectivity, intersections, and obstacles significantly influence navigation performance.

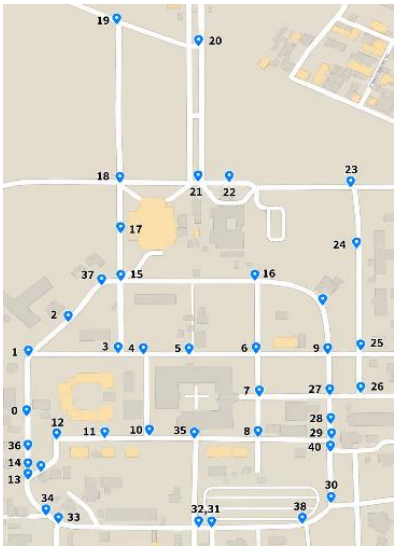


Figure 1. Route map Universitas Sriwijaya, Indralaya Campus

The proposed method was implemented using visual studio code with Flutter for mobile application development and PHP MySQL for server-side processing. Google Maps API was utilized for map visualization and routing services, while Firebase Authentication managed user authentication. The experiments were performed on a computer equipped with an Intel Core i7 processor, 16 GB RAM, and Windows 11 operating system. These specifications ensure that the reported computation time can be reproduced under similar computational environments.

The parameters used in the proposed IACO shows in Table 1, including the number of ants, pheromone evaporation rate, pheromone influence coefficient (α), heuristic influence coefficient (β), and maximum number of iterations, were determined based on a combination of previous studies and preliminary experiments. Initially, parameter ranges reported in established ACO literature were adopted as reference values. Subsequently, several preliminary experiments were conducted on representative routes within the study area to identify parameter combinations that consistently produced stable convergence, short computation time, and accurate path generation. The final parameter settings were selected because they provided the best overall balance between solution quality and computational efficiency.

Table 1. Testing parameters

Improved ACO	Traditional ACO
The amount of ant=50 ants	The amount of ant=50 ants
The amount of iteration=30 iteration	the amount of iteration=30 iteration
The maximum number of pheromone steps=50	The maximum number of pheromone steps=50
Evaporation rate=0.1	Evaporation rate=0.1
Alpha=0.7	Alpha=0.7
Beta=0	Beta=0.3

The evaluation criteria were separated between obstacle-free and obstacle-present conditions. Under obstacle-free conditions, the OpenStreetMap (OSM)-referenced route distance was used as a common reference for comparing the generated routes. Under obstacle-present conditions, the introduction of an obstacle changed the set of feasible routes, and an independent ground-truth optimal route was not available. Consequently, OSM-based distance deviation was not interpreted as an accuracy measure for the obstacle scenarios.

Instead, obstacle-present experiments were evaluated based on whether the planner successfully generated an alternative feasible route, the additional distance resulting from route diversion, and the time

required to regenerate the route. These measures provide a more appropriate assessment of the planner's ability to respond to changes in road traversability. The distinction prevents obstacle-avoidance capability from being conflated with absolute route optimality.

3.2. Results without obstacles

Table 2 dan Figure 2 presents the path planning results for the obstacle-free scenario, where both algorithms are compared against OSM as the reference ground truth. OSM was used as a reference for evaluating route distances under obstacle-free conditions. For each origin–destination pair, the same locations were used to obtain the corresponding OSM-referenced route distance. The distance generated by IACO and the baseline ACO method was then compared with this reference, and the absolute deviation was calculated to quantify the difference between the generated route and the OSM-referenced distance.

OSM is used in this study as a reference representation of the road network rather than as an absolute ground truth for path optimality. An OSM-derived route may depend on the completeness of the mapped road network, available road attributes, and the routing procedure used to obtain the route. Therefore, a smaller deviation from the OSM reference indicates greater conformity to the reference route distance, but does not establish that the generated route is globally optimal or physically shortest. Overall, the results indicate that IACO consistently produces paths that are closer to the reference map compared to traditional ACO (TACO).

Table 2. Testing result without obstacle

No.	Initial	Goal	IACO (m)	TACO (m)	OSM map (m)
1	Auditorium	Language Institution	240	240	240
2	Auditorium	Faculty of Agriculture	842.04	1006.4	855.9
3	Auditorium	Faculty of Economic	739	739	739
4	Monument of UNSRI	Library	539	1069	539
5	Monument of UNSRI	Faculty of Social Sciences and Political Science	373	373	373
6	Monument of UNSRI	Faculty of Mathematics and Natural Science	755.7	1284.1	755.7
7	Rectorate	Bus station	853	983	853
8	Rectorate	Library	610.4	737.33	610.4
9	Faculty of Social Sciences and Political Science	Faculty of Engineering	724.5	876.06	724.5
10	Faculty of Social Sciences and Political Science	Faculty of Teacher Training and Education	618	693	618
11	Faculty of Economic	Faculty of Medicine	634.4	713.4	634.4
12	Faculty of Economic	Fishery Department	212.3	212.3	212.3
13	Bus station	Auditorium	699.38	699.38	699.38
14	Bus station	Faculty of Social Sciences and Political Science	654.39	654.39	654.39
15	Faculty of Engineering	Fishery Department	460.72	469.72	460.72
16	Faculty of Engineering	Language Institution	308	296.7	296.7
17	Faculty of Mathematics and Natural Science	Faculty of Economic	570.1	570.1	570.1
18	Faculty of Mathematics and Natural Science	Library	505	505	511
19	Faculty of Agriculture	Faculty of Social Sciences and Political Science	797	797	778
20	Faculty of Agriculture	Monument of UNSRI	1006	1101	983
21	Faculty of Teacher Training and Education	Fishery Department	234.9	234.9	234.9
22	Faculty of Teacher Training and Education	Medical Faculty	699.2	699.2	699.2
23	Library	Auditorium	456.3	456.3	456.3
24	Library	Faculty of Engineering	316.01	316.01	316.01
25	Faculty of Medicine	Auditorium	316.35	316.35	316.35
26	Faculty of Medicine	Faculty of Agriculture	539.6	737.5	539.6
27	Library	Faculty of Economic	543.5	543.5	543.5
28	Library	Faculty of Mathematics and Natural Science	503	492	492
29	Fishery Department	Faculty of Agriculture	245	245	245
30	Fishery Department	Auditorium	609.4	609.4	609.4

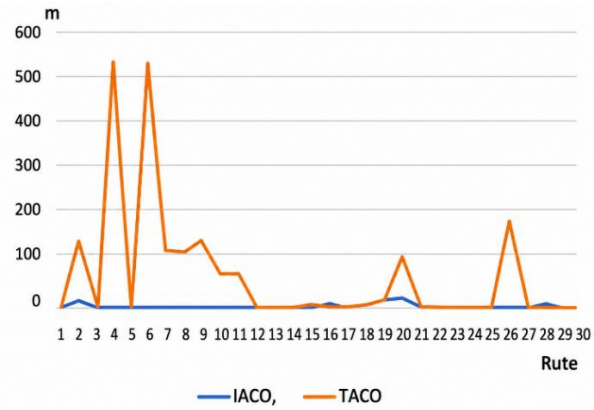


Figure 2. Absolute distance error for all routes

Distinction is particularly important in interpreting the accuracy results. The reported error represents deviation from the selected reference rather than an absolute optimality error. Accordingly, the OSM-based evaluation is used to assess the consistency of the proposed method with an established digital road-network representation.

Form Table 2 we generate absolute distance error chart is shown in Figure 2. The error is calculated by comparing the distances obtained using the IACO and the TACO with the OSM as the reference setpoint. As illustrated in the Figure 2, the distance error of the IACO is smaller than that of the TACO. The spike in red indicates that the TACO struggles with longer distances, with the highest errors occurring in the 4th and 6th routes, reaching 530 m and 528.4 m, respectively. This suggests that the IACO, by setting the heuristic factor to zero, may prevent the algorithm from becoming trapped in local minima, unlike the traditional ACO, which exhibits higher errors.

The error distribution shows in Figure 3 that IACO maintains stable and low deviations across all routes, with a mean absolute error (MAE) of 2.8 m. In contrast, TACO exhibits significantly higher variability, with an MAE of 70.7 m. This large difference indicates that TACO is more susceptible to suboptimal convergence, particularly in routes with multiple intersections and longer distances.

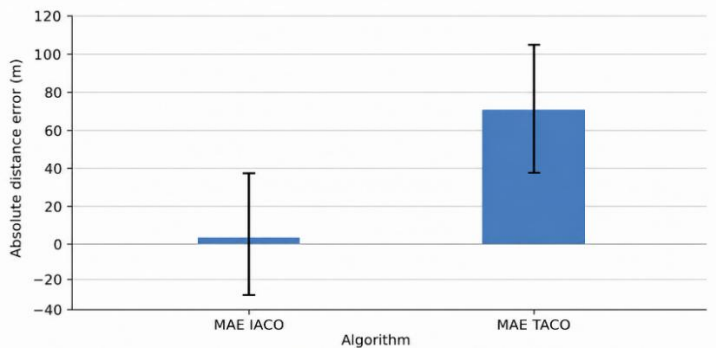


Figure 3. MAE

The performance degradation of TACO becomes more evident in complex routes, where it produces substantially larger errors (e.g., up to 530 m and 528.4 m in specific cases). This behavior suggests that traditional ACO is prone to local minima when exploring large search spaces. In contrast, the proposed IACO mitigates this issue by eliminating the heuristic distance influence (β=0), allowing pheromone-driven exploration to dominate the decision-making process.

For simpler routes with fewer intersections, both algorithms occasionally produce similar results, indicating that in low-complexity environments, the advantage of the proposed method becomes less pronounced. In terms of computational efficiency shows in Figure 4, IACO significantly outperforms TACO. The average route generation time of IACO is 0.47 s, while TACO requires approximately 2.47–2.52 s. This confirms that the proposed graph–grid integration reduces computational overhead by limiting unnecessary exploration in the search space.

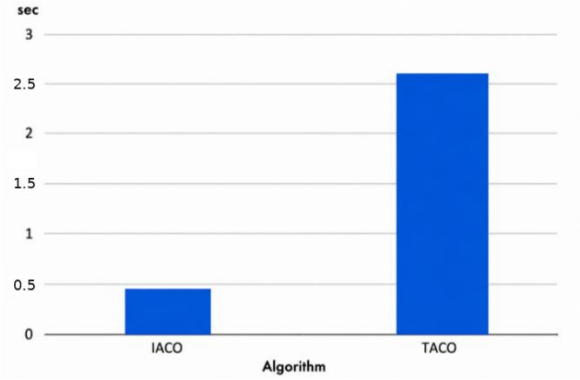


Figure 4. Route generation time difference without obstacle (in s)

3.3. Results with obstacles

Obstacles were introduced into the road network to evaluate the capability of the proposed IACO to adapt the planned path when the initially selected path became unavailable. Three obstacle types were considered: motorcycles, cars, and road blockages, representing common temporary obstructions encountered in road environments. The obstacles were placed on selected road segments along the planned paths to prevent direct traversal through the affected locations. For motorcycle and car obstacles, the affected road segment was considered temporarily unavailable for path traversal, whereas a road blockage represented a more restrictive obstruction that prevented passage through the corresponding road segment. The same obstacle configurations were applied to the evaluated methods to ensure a consistent experimental condition. When an obstacle blocked the initially selected path, the planner was required to identify an alternative feasible path through the available connected nodes. The obstacle experiments were therefore used to evaluate path adaptation and obstacle avoidance capability, rather than absolute global path optimality.

Table 3 presents the results for the obstacle scenario, where obstacles such as roadblocks and vehicles are introduced to evaluate rerouting capability. Since OSM does not support dynamic rerouting, it is excluded from this comparison. The results demonstrate that IACO consistently outperforms TACO in terms of rerouting efficiency and path optimality. In complex environments, IACO is able to identify shorter alternative routes when obstacles block the original path. For instance, in Route 29, IACO produces a significantly shorter path (560 m) compared to TACO (1045 m), indicating stronger adaptability in dynamic environments.

However, for simple routes with minimal intersection such us in Route 10, both algorithms may produce similar path lengths, indicating that the benefit of the proposed method is more evident in complex scenarios with multiple intersections and obstacles. Figure 5 illustrates the comparison of average route generation time between both methods. The results confirm that IACO significantly reduces computational time compared to TACO.

Specifically, IACO requires only 0.47 s (no obstacle) and 0.21 s (with obstacles), whereas TACO requires 2.52 s (without obstacle) and 5.12 s (with obstacle), respectively. The increase in TACO computation time under obstacle conditions indicates higher sensitivity to search space complexity, leading to increased iteration requirements.

This improvement is attributed to the hybrid graph–grid representation, which reduces the number of decision nodes and therefore lowers the computational burden during probability calculation. As a result, IACO achieves faster convergence while maintaining or improving path quality.

3.4. Discussion

The experimental results demonstrate that the proposed IACO provides a consistent improvement over traditional ACO in terms of both accuracy and efficiency. The reduction in MAE indicates improved path optimality, while the significant decrease in computation time confirms the efficiency of the proposed hybrid representation.

The main reason for this improvement lies in two key modifications: i) integration of graph and grid representations, which balances search space reduction and environmental resolution and ii) elimination of the heuristic distance factor (β=0), which reduces bias toward local minima and improves exploration capability.

Table 3. Testing result with obstacle

No.	Initial	Goal	MACO (m)	TACO (m)
1	Auditorium	Language Institution	1268	1309
2	Auditorium	Faculty of Agriculture	1395	1936
3	Auditorium	Faculty of Economic	585	1115
4	Monument of UNSRI	Library	567	1023
5	Monument of UNSRI	Faculty of Social Sciences and Political Science	408	408
6	Monument of UNSRI	Faculty of Mathematics and Natural Science	638	835
7	Rectorate	Bus station	577	756
8	Rectorate	Library	754	977
9	Faculty of Social Sciences and Political Science	Faculty of Engineering	706	858
10	Faculty of Social Sciences and Political Science	Faculty of Teacher Training and Education	322	322
11	Faculty of Economic	Faculty of Medicine	757	1108
12	Faculty of Economic	Fishery Department	413	863
13	Bus station	Auditorium	878	998
14	Bus station	Faculty of Social Sciences and Political Science	715	908
15	Faculty of Engineering	Fishery Department	547	744
16	Faculty of Engineering	Language Institution	262	780
17	Faculty of Mathematics and Natural Science	Faculty of Economic	653	729
18	Faculty of Mathematics and Natural Science	Library	724	770
19	Faculty of Agriculture	Faculty of Social Sciences and Political Science	719	719
20	Faculty of Agriculture	UNSRI Monument	1056	1389
21	Faculty of Teacher Training and Education	Fishery Department	562	657
22	Faculty of Teacher Training and Education	Medical Faculty	682	682
23	Library	Auditorium	861	1110
24	Library	Faculty of Engineering	559	559
25	Faculty of Medicine	Auditorium	1168	1426
26	Faculty of Medicine	Faculty of Agriculture	647	1008
27	Library	Faculty of Economic	246	549
28	Library	Faculty of Mathematics and Natural Science	505	609
29	Fishery Department	Faculty of Agriculture	560	1045
30	Fishery Department	Auditorium	738	1219

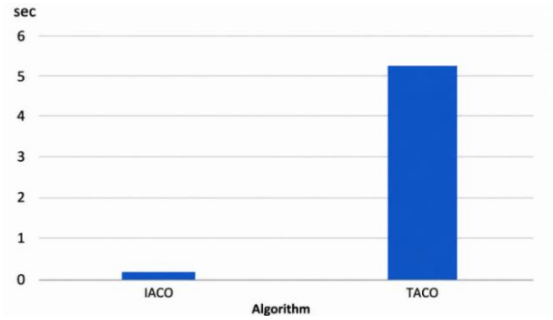


Figure 5. Average route generation time (s)

Although the proposed framework was evaluated on the Universitas Sriwijaya campus road network, its graph-based representation is not inherently limited to campus-scale environments. The road network is represented using relevant graph nodes, such as intersections and turning points, which enables the search space to remain compact as the network expands. The grid principle is incorporated through the modified node-transition probability, in which the direct distance-related component is assigned a zero value to reduce the preference for geographically closer nodes. Thus, the proposed approach does not require probability calculations for individual grid cells. As the network size increases, the computational cost is expected to depend primarily on the number of graph nodes, edges, and search iterations. Nevertheless, the scalability of the proposed framework has not yet been experimentally validated on city-scale networks and therefore requires further investigation.

Compared with conventional ACO, the proposed IACO provides a less distance-biased node-selection mechanism while retaining the computational advantage of graph-based search. By removing the direct distance-related component from the transition probability, the algorithm can explore alternative connected nodes without requiring cell-by-cell grid evaluation. This modification is intended to reduce the tendency of graph-based ACO to favor geographically closer nodes and consequently improve path exploration while maintaining low path-planning time. The proposed framework should therefore be regarded as a graph-based ACO with a grid-inspired exploration principle rather than a conventional combination of graph and cell-level grid search.

The proposed approach is particularly relevant to road environments with irregular connectivity and multiple alternative paths, such as suburban road networks. Its compact graph representation can reduce the computational burden associated with exhaustive grid-based search, while the modified transition probability provides greater exploration flexibility than a distance-driven graph search. However, the present evaluation is limited to a single university campus and relatively controlled experimental conditions. Therefore, further experiments on larger and more diverse urban and suburban road networks, including dynamic obstacles, traffic conditions, and real-time sensor observations, are required to determine the scalability and generalizability of the proposed framework for autonomous vehicle path planning.

3.5. Limitations and future work

Despite the encouraging results, this study has several limitations. First, the experimental evaluation was conducted on a single university campus road network, which may not fully represent the structural diversity of urban and suburban road environments. Second, the experimental obstacles were introduced under relatively controlled and static conditions, whereas real autonomous vehicles operate in environments containing dynamic vehicles, pedestrians, and other time-varying obstacles. Third, the current evaluation focuses primarily on route planning and does not comprehensively evaluate the interaction between planning, localization uncertainty, perception errors, and vehicle control. Finally, the scalability of the proposed framework for substantially larger road networks has not yet been systematically investigated.

Future research should therefore evaluate the proposed framework on larger and more diverse urban road networks, incorporate dynamic and unpredictable obstacles, and integrate real-time sensor observations with localization and vehicle-control systems. Such evaluations are necessary to determine the robustness, scalability, and generalizability of the proposed approach under realistic autonomous-driving conditions.

4. CONCLUSION

This study proposed an IACO strategy within a hybrid graph–grid framework for accurate and low-latency path planning. The main methodological contribution is the modification of the node-transition probability by assigning zero to the direct distance-related component. This reduces the preference for geographically closer nodes and promotes broader exploration of connected alternatives. Unlike conventional grid-based path planning, the proposed approach retains a graph-based search structure, where probability calculations are performed only at relevant road nodes, such as intersections and turning points, rather than across individual grid cells. This design incorporates a grid-inspired exploration principle while preserving the computational efficiency of graph-based path planning.

The quantitative results demonstrate the effectiveness of the proposed approach under the evaluated conditions. IACO achieved a MAE of 2.8 m relative to the OSM reference, compared with 70.7 m for TACO. The proposed method also reduced the average path-generation time from 0.47 s for TACO to 0.21 s for IACO. Under obstacle-present conditions, IACO was able to generate alternative feasible paths when the initially selected path became unavailable. The framework was further implemented and evaluated through a mobile application, demonstrating its potential for practical path-planning applications.

These findings indicate that reducing distance-related bias in the node-transition probability can improve exploration within graph-based ACO while avoiding the computational burden of cell-by-cell grid search. Nevertheless, the results should be interpreted within the scope of the experiments. The OSM data were used as a reference for path-distance comparison rather than as ground truth for global path optimality, while the obstacle experiments evaluated path adaptation rather than absolute optimality. In addition, the evaluation was conducted on a single university campus road network under relatively controlled conditions. Therefore, the results provide promising preliminary evidence of the proposed IACO framework rather than definitive validation of real-time autonomous navigation in general environments.

Future work will focus on evaluating the proposed framework on larger and more diverse road networks, as well as under dynamic obstacles, traffic conditions, and real-time sensor observations. Further integration with localization, perception, and vehicle-control systems will also be investigated to assess the robustness, scalability, and practical applicability of the proposed IACO framework for autonomous vehicle path planning.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
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O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

REFERENCES

[1] C. Gu, A. Feng, G. Wang, and X. Liu, "Robot Path Planning of Improved Adaptive Ant Colony System Algorithm Based on Dijkstra," *Journal of Robotics*, pp. 1–11, Dec. 2022, doi: 10.1155/2022/9229155.

[2] C. Zong, X. Yao, and X. Fu, "Path Planning of Mobile Robot based on Improved Ant Colony Algorithm," in *2022 IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, Chongqing, China: IEEE, Jun. 2022, pp. 1106–1110, doi: 10.1109/ITAIC54216.2022.9836572.

[3] K. Shi *et al.*, "Path Planning Optimization of Intelligent Vehicle Based on Improved Genetic and Ant Colony Hybrid Algorithm," *Frontiers in Bioengineering and Biotechnology*, vol. 10, pp. 1–17, Jul. 2022, doi: 10.3389/fbioe.2022.905983.

[4] A. Gupta and S. Srivastava, "Comparative Analysis of Ant Colony and Particle Swarm Optimization Algorithms for Distance Optimization," *Procedia Computer Science*, vol. 173, pp. 245–253, 2020, doi: 10.1016/j.procs.2020.06.029.

[5] G. Che, L. Liu, and Z. Yu, "An improved ant colony optimization algorithm based on particle swarm optimization algorithm for path planning of autonomous underwater vehicle," *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 8, pp. 3349–3354, Aug. 2020, doi: 10.1007/s12652-019-01531-8.

[6] G. Chikun, Y. Yuhang, Y. Lipeng, and W. Jiaxin, "An improved ant colony algorithm for integrating global path planning and local obstacle avoidance for mobile robot in dynamic environment," *Mathematical Biosciences and Engineering*, vol. 19, no. 12, pp. 12405–12426, 2022, doi: 10.3934/mbe.2022579.

[7] D. Di Caprio, A. Ebrahimnejad, H. Alrezaamiri, and F. J. Santos-Arteaga, "A novel ant colony algorithm for solving shortest path problems with fuzzy arc weights," *Alexandria Engineering Journal*, vol. 61, no. 5, pp. 3403–3415, May 2022, doi: 10.1016/j.aej.2021.08.058.

[8] Y. Tao *et al.*, "A mobile service robot global path planning method based on ant colony optimization and fuzzy control," *Applied Sciences*, vol. 11, no. 8, pp. 1–15, Apr. 2021, doi: 10.3390/app11083605.

[9] Q. Jin, C. Tang, and W. Cai, "Research on Dynamic Path Planning Based on the Fusion Algorithm of Improved Ant Colony Optimization and Rolling Window Method," *IEEE Access*, vol. 10, pp. 28322–28332, 2022, doi: 10.1109/ACCESS.2021.3064831.

[10] W. Wang, X. Yin, S. Wang, J. Wang, and G. Wen, "Robot Path Planning Method Combining Enhanced APF and Improved ACO Algorithm for Power Emergency Maintenance," *International Journal of Information Technologies and Systems Approach*, vol. 16, no. 3, pp. 1–17, Jul. 2023, doi: 10.4018/IJITSA.326552.

[11] G. Chen and J. Liu, "Mobile Robot Path Planning Using Ant Colony Algorithm and Improved Potential Field Method," *Computational Intelligence and Neuroscience*, pp. 1–10, May 2019, doi: 10.1155/2019/1932812.

[12] Y. Chen, W. Luo, M. Wang, Y. Su, and H. Zhang, "UUV 3D Path Planning Based on PSO-ACO Fusion Algorithm," in *2022 37th Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, Beijing, China: IEEE, Nov. 2022, pp. 599–604, doi: 10.1109/YAC57282.2022.10023579.

[13] H. Ali, D. Gong, M. Wang, and X. Dai, "Path Planning of Mobile Robot With Improved Ant Colony Algorithm and MDP to Produce Smooth Trajectory in Grid-Based Environment," *Frontiers in Neurorobotics*, vol. 14, pp. 1–13, Jul. 2020, doi: 10.3389/fnbot.2020.00044.

[14] J. Fu, T. Lv, and B. Li, "Underwater Submarine Path Planning Based on Artificial Potential Field Ant Colony Algorithm and Velocity Obstacle Method," *Sensors*, vol. 22, no. 10, p. 3652, May 2022, doi: 10.3390/s22103652.

[15] M. Li, B. Li, Z. Qi, J. Li, and J. Wu, "Optimized APF-ACO Algorithm for Ship Collision Avoidance and Path Planning," *Journal of Marine Science and Engineering*, vol. 11, no. 6, p. 1177, Jun. 2023, doi: 10.3390/jmse11061177.

[16] T. W. Zhang, G. H. Xu, X. S. Zhan, and T. Han, "A new hybrid algorithm for path planning of mobile robot," *Journal of Supercomputing*, vol. 78, no. 3, pp. 4158–4181, Feb. 2022, doi: 10.1007/s11227-021-04031-9.
[17] X. Yu, W. N. Chen, T. Gu, H. Yuan, H. Zhang, and J. Zhang, "ACO-A∗: Ant Colony Optimization plus A∗ for 3-D Traveling in Environments with Dense Obstacles," *IEEE Transactions on Evolutionary Computation*, vol. 23, no. 4, pp. 617–631, Aug. 2019, doi: 10.1109/TEVC.2018.2878221.
[18] W. Gao, Q. Tang, B. Ye, Y. Yang, and J. Yao, "An enhanced heuristic ant colony optimization for mobile robot path planning," *Soft Computing*, vol. 24, no. 8, pp. 6139–6150, Apr. 2020, doi: 10.1007/s00500-020-04749-3.
[19] J. Yu *et al*., "A Novel Parallel Ant Colony Optimization Algorithm for Warehouse Path Planning," *Journal of Control Science and Engineering*, pp. 1–12, Aug. 2020, doi: 10.1155/2020/5287189.
[20] J. Cheng, "Dynamic Path Optimization Based on Improved Ant Colony Algorithm," *Journal of Advanced Transportation*, no. 1, Jan. 2023, doi: 10.1155/2023/7651100.
[21] X. Li, Q. Li, and J. Zhang, "Research on global path planning of unmanned vehicles based on improved ant colony algorithm in the complex road environment," *Measurement and Control (United Kingdom)*, vol. 55, no. 9–10, pp. 945–959, Nov. 2022, doi: 10.1177/00202940221118132.
[22] Y. Wang, X. Lu, and Z. Zuo, "Autonomous vehicles path planning with enhanced ant colony optimization," in *2019 Chinese Control Conference (CCC)*, Guangzhou, China: IEEE, Jul. 2019, pp. 6633–6638, doi: 10.23919/ChiCC.2019.8866128.
[23] L. Wu, X. Huang, J. Cui, C. Liu, and W. Xiao, "Modified adaptive ant colony optimization algorithm and its application for solving path planning of mobile robot," *Expert Systems with Applications*, vol. 215, p. 119410, Apr. 2023, doi: 10.1016/j.eswa.2022.119410.
[24] Y. Chen, G. Bai, Y. Zhan, X. Hu, and J. Liu, "Path Planning and Obstacle Avoiding of the USV Based on Improved ACO-APF Hybrid Algorithm with Adaptive Early-Warning," *IEEE Access*, vol. 9, pp. 40728–40742, 2021, doi: 10.1109/ACCESS.2021.3062375.
[25] T. Lei, C. Luo, J. E. Ball, and S. Rahimi, "A Graph-based Ant-like Approach to Optimal Path Planning," in *2020 IEEE Congress on Evolutionary Computation (CEC)*, Glasgow, UK: IEEE, Jul. 2020, pp. 1–6, doi: 10.1109/CEC48606.2020.9185628.
[26] X. Tan and D. Chen, "A hybrid approach of path planning for mobile robots based on the combination of ACO and APF algorithms," in *2009 International Workshop on Intelligent Systems and Applications*, Wuhan, China: IEEE, May 2009, pp. 1–4, doi: 10.1109/IWISA.2009.5072623.
[27] Z. Cai, J. Liu, L. Xu, and J. Wang, "Cooperative path planning study of distributed multi-mobile robots based on optimised ACO algorithm," *Robotics and Autonomous Systems*, vol. 179, p. 104748, Sep. 2024, doi: 10.1016/j.robot.2024.104748.

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