ENHANCED KNOWLEDGE IN SCIENCES AND TECHNOLOGY
e-ISSN: 2773-6385

EKST

Vol. 6 No. 1 (2026) 142-149
https://publisher.uthm.edu.my/periodicals/index.php/ekst

Optimizing the Shortest Route Problem in Pagoh Using Ant Colony Optimization Algorithm

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DOI: https://doi.org/10.30880/ekst.2026.06.01.018

Article Info

Received: 4 January 2026
Accepted: 20 January 2026
Available online: 9 July 2026

Keywords

Shortest Route Problem, Ant Colony Optimization, Graph Model, Road Network

Abstract

Efficient route planning is important for managing movement within areas that have interconnected road networks, such as Pagoh. Drivers and visitors may have trouble identifying the most suitable routes due to limited navigation guidance and reliance on static maps. This study addresses the Shortest Route Problem (SRP) by applying an optimization-based approach. The objective of this study is to construct a graph-based model of selected roads in Pagoh and to implement the Ant Colony Optimization (ACO) algorithm to determine the shortest route between a starting point and a destination. The scope of the study is limited to a simplified road network with selected nodes. The road network is modelled as a weighted graph, where nodes represent key locations and road junctions, and edges represent road connections. The edge weights are based on physical distances calculated using latitude and longitude data obtained from Google Maps and the Haversine formula. The Ant Colony Optimization (ACO) algorithm is then applied to identify the shortest route from node A to node I. The results indicate that the ACO algorithm successfully identified the route A → C → E → H → I as the shortest path, with a total distance of 2.70 km. The results show that the ACO algorithm can identify an efficient route with the minimum travel distance within the defined network. This study demonstrates the applicability of ACO as a graph-based approach for solving the shortest route problem in a simplified road network and provides a basis for further improvement in future studies.

1. Introduction

Efficient route selection is an important aspect of road network management, particularly in areas with multiple junctions and alternative paths. In such environments, drivers often rely on personal experience or static navigation aids, which may not always lead to efficient route choices. This issue is commonly observed in developing towns and semi-urban areas where road networks are gradually expanding and becoming more complex.

From a theoretical perspective, route selection problems are commonly formulated as the Shortest Route Problem (SRP), which focuses on identifying the minimum-distance path between two locations within a network [1]. Conventional approaches to solving SRP are typically based on graph theory. Among optimization-based methods, Ant Colony Optimization (ACO) is a nature-inspired optimization technique developed based on the foraging behaviour of ants [2],[3]. Through pheromone-based communication, ants can discover shorter paths between their nest and food sources. This collective behaviour has been translated into a computational algorithm that can explore multiple paths probabilistically and improve solution quality through iterative learning [4]. Due to these characteristics, ACO has been applied to various routing and path-finding problems, including transportation networks and navigation systems [5],[6].

In practical road networks, route selection becomes more challenging when multiple junctions and alternative paths exist. Pagoh is a developing town in Johor that consists of residential areas, main roads, and local connecting streets. Navigating within this road network can be challenging, especially for users who are unfamiliar with the area and must choose between several possible routes. Under such conditions, relying solely on static navigation information may not always result in efficient travel paths.

Therefore, this study focuses on constructing a graph-based model of the Pagoh road network using nodes and weighted edges and implementing the ACO algorithm to solve the shortest route problem within the selected area. The road network is modelled as a weighted graph, where nodes represent selected locations and junctions, while edge weights are determined based on travel distance.

This research involves representing the selected road network as a graph, applying the ACO algorithm in a simulation environment, and analysing the generated routes based on total distance. The expected outcome of this study is the identification of an efficient route between selected locations in Pagoh, demonstrating the applicability of ACO for solving the shortest route problem in a graph-based road network.

2. Methodology

This study employs a quantitative, simulation-based approach to address the shortest route problem in the Pagoh road network using the Ant Colony Optimization (ACO) algorithm. The selected road network is represented as a graph structure, were nodes and weighted edges model locations and road connections, respectively. The optimization process is carried out through algorithmic simulation, in which the ACO algorithm mimics the foraging behaviour of ants by using pheromone trails to guide route selection. The simulation begins with the initialization of the graph and algorithm parameters, followed by the exploration of multiple possible routes by artificial ant agents. Pheromone values are then updated based on the quality of the routes obtained, and this process is repeated iteratively until a stable solution is achieved.

2.1 Study Area and Data Collection

This study considers a selected road network in Pagoh, Johor, Malaysia. The road network is modelled as a weighted directed graph, where nodes represent key locations or road junctions and directed edges represent road segments connecting the nodes. Edge directions follow actual traffic flow conditions, consistent with common graph-based representations used in routing and network analysis [1].

The identified nodes and their corresponding locations are listed in Table I. The distances between connected nodes were obtained using Google Maps and are used as edge weights in the routing model. Representing physical distance as edge weight is a standard approach in shortest route and network optimization studies [3]. The distance between node i and node j is defined as:

$$d_{ij} = \text{distance between node } i \text{ and node } j$$

Table 1 lists the nodes representing key locations and junctions in the Pagoh road network. Each node corresponds to a significant point in the road network, and these nodes serve as vertices in the graph-based representation used for route optimization. The selection of nodes ensures that the model captures relevant connectivity and commonly used travel paths within the study area, as suggested in graph modelling practices for transportation networks [5].

Table 1 Node Identifications

Node	Locations
A	Tiny Cottage Pagoh
B	Jalan Batin
C	Jalan Kampung Raja
D	Jalan Sekolah
E	Jalan Muar-Labis
F	Jalan Haji Yusuf
G	Lorong Haji Abdul Aziz Sidin
H	Jalan Pagoh Jaya
I	Taman Pagoh Jaya

In this study, nodes are defined as key locations and road junctions within the selected study area in Pagoh. Each node represents a significant point in the road network that contributes to route connectivity.

Table 2 Road Connection and Distance Identification

From	To	Distance(km)
A	B	0.70
A	C	0.30
A	D	0.13
B	E	1.10
C	E	0.80
C	G	1.20
D	F	0.55
E	H	0.90
F	G	0.45
G	E	0.60
H	I	0.70

Table 2 presents the distances between directly connected nodes, which are used as edge weights in the graph representation. The distances, measured in kilometres using Google Maps, provide the heuristic information required by the Ant Colony Optimization (ACO) algorithm for evaluating the relative efficiency of different routes. Shorter distances correspond to higher attractiveness for route selection by simulated ants.

After identifying the nodes, the road connections between nodes were determined based on the road layout. The distance between each pair of connected nodes was then determined to represent the travel length between locations. These distances are later used as edge weights in the routing model. The edge weights are based on physical distances calculated using latitude and longitude data obtained from Google Maps and the Haversine formula.

2.2 Ant Colony Algorithm Optimization

The Ant Colony Optimization (ACO) algorithm is based on the natural behaviours of ants in discovering the shortest path to food sources. Artificial ants are employed in this research as agents that explore a graph-based road network to identify optimal routes between selected locations [1], [3].

The ACO algorithm is widely used to identify efficient routing paths within complex networks. It is a nature-inspired optimization technique based on collective foraging behaviours, where pheromone trails deposited by ants influence subsequent path selection [7], [8].

Artificial ants traverse the weighted directed graph to construct routes between selected origin and destination nodes. The probability P_{ij} of an ant moving from node $i$to node j is defined as:

$$P_{ij} = \frac{(\tau_{ik})^{\alpha}(\eta_{ik})^{\beta}}{\sum_{k\in N_i}(\tau_{ik})^{\alpha}(\eta_{ik})^{\beta}}$$

where τ_{ij} is the pheromone intensity, $\eta_{ij} = 1/d_{ij}$ is the heuristic value based on distance, α and β control the influence of pheromone and distance, and N_i denotes feasible neighbouring nodes.

After each iteration, pheromone levels are updated through evaporation and reinforcement:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{m} \Delta\, \tau_{ij}^{k}$$

where ρ is the pheromone evaporation rate, m is the number of ants, and $\Delta\tau_{ij}^{k}$ represents the pheromone contribution of ant k based on route quality [8].

The algorithm is executed iteratively to generate multiple candidate routes. Routes with shorter total distances receive higher pheromone reinforcement, while less efficient routes gradually lose influence due to pheromone evaporation. This iterative process allows the algorithm to converge toward an optimal solution over time [10].

Initially, pheromone values on all paths are set equally. As the algorithm progresses, ants move between nodes based on pheromone concentration and distance information. Shorter paths receive greater pheromone reinforcement, increasing their likelihood of being selected in subsequent iterations [1], [3].

Pheromone evaporation plays an important role in preventing premature convergence by reducing the influence of previously selected paths, while reinforcement encourages exploration of promising routes. This balance between exploration and exploitation continues until a stable optimized route is identified within the network [9].

To translate the theoretical concept of ACO into a practical routing solution, the algorithm is implemented through a sequence of systematic steps. These steps govern the initialization of parameters, route construction by artificial ants, and pheromone updating mechanisms used in this study [10].

Step 1: The algorithm parameters are initialized, including the number of ants, maximum number of iterations, pheromone evaporation rate ρ, initial pheromone value τ_0, and the relative influence of pheromone intensity and heuristic information. A pheromone matrix is created with uniform initial values.

Step 2: Artificial ants are positioned at the designated starting node in the graph-based network.

Step 3: At each node, an ant selects the next node to visit based on a probabilistic decision rule that considers both pheromone concentration and distance-based heuristic information, as defined by Equations (1)– (3)

$$p_{ij} = \frac{(\tau_{ij})^{\alpha}.(n_{ij})^{\beta}}{\sum(\tau_{ij})^{\alpha}.(n_{ij})^{\beta}} \tag{1}$$

$$P_{k(i,j)} = \arg - \max\{(\tau_{iz}).(n_{iz})^{\beta}\} \tag{2}$$

$$P_{k(i,j)} = \left\{\frac{(\tau_{ij}).(n_{ij})^{\beta}}{\sum_{z\in jk}(i)(\tau_{iz}).(n_{iz})^{\beta}}\right\} \tag{3}$$

Step 4: This selection process continues until the destination node is reached. Once a complete route is formed, the total distance travelled by the ant is calculated and a local pheromone update is applied to the visited edges.

$$\tau_{IJ} = (1 - \rho) * \tau_{IJ} + \rho * \tau_0, \tag{4}$$

Step 5: After all ants complete their routes in one iteration, a global pheromone update is performed. Edges belonging to shorter routes receive higher pheromone reinforcement, while pheromone levels on other paths are reduced through evaporation.

$$\tau_{IJ} = (1 - \rho) * \tau_{IJ} + \rho(1_{mc})^{-1} \tag{5}$$

Step 6: The process is repeated over multiple iterations until the stopping criterion is met, after which the route with the shortest total distance is selected as the optimal solution.

2.3 Simulation and Optimization Process

The simulation of the Ant Colony Optimization (ACO) algorithm was implemented using Python. Python was selected due to its flexibility and suitability for algorithm-based simulations and graph modelling. This simulation is conducted using a population of artificial ants that construct candidate paths within the graph over multiple iterations. Each ant generates a route between selected origin and destination nodes, and the total distance of each route is calculated. Shorter routes receive greater pheromone reinforcement, increasing their probability of selection in subsequent iterations [7], [11].

Important variables like the strength of the ant population, the effect of the pheromone, and the evaporation rate can be varied to ensure stable outputs. The simulation process enables the algorithm to improve towards the optimal route over several runs.

Key parameters such as ant population size, pheromone influence, and evaporation rate are adjusted to ensure stable and consistent results. Through repeated simulations, the algorithm gradually improves solution quality by balancing route exploration and exploitation [9]. By running the algorithm over multiple iterations, the ants initially explore various possible routes before converging toward paths with shorter distances. This iterative optimization process enhances the likelihood of identifying an optimal or near-optimal route within the road network [12].

3. Results and Discussion

In this section, the findings of the implementation of the Ant Colony Optimization (ACO) algorithm on the shortest route problem in the Pagoh will be shown. The findings will be explained in relation to the graph-based concept modelled and the optimal routes determined from the algorithm.

3.1 Graph-Based Representation of Pagoh

To enable the application of the Ant Colony Optimization (ACO) algorithm, the road network of Pagoh was abstracted into a graph-based model. This approach maps real locations in the town into a structured system, reducing the complexity of the physical environment and facilitating route analysis.

In this model, key geographic points in Pagoh are represented as nodes, and the roads connecting them are represented as edges. Each edge is assigned a weight corresponding to the distance in kilometres between two connected locations. These weights serve as critical inputs for the ACO algorithm, allowing the evaluation of route efficiency based on actual distances.

Nine locations were selected as nodes in this study. There are Tiny Cottage Pagoh, Jalan Batin, Jalan Kampung Raja, Jalan Sekolah, Jalan Muar–Labis, Jalan Haji Yusof, Lorong Haji Abdul Aziz Sidin, Jalan Pagoh Jaya, and Taman Pagoh Jaya. These locations were chosen due to their high accessibility within the town and their relevance to typical travel patterns.

Fig 1 illustrates the constructed network graph. Each node is connected to other nodes via weighted edges, representing the possible travel paths within Pagoh.

All relevant connections, including the direct link between node C and node E (0.8 km), are included to ensure the model captures alternative paths available in the actual road network. The inclusion of multiple edges allows for meaningful route analysis and ensures that the ACO algorithm can explore various candidate paths to determine efficient routing solutions.

Overall, this graph-based abstraction provides a simplified yet structured representation of Pagoh road network. While certain assumptions are made regarding distances, the model accurately reflects the connectivity of key locations and forms a foundation for subsequent optimization analysis using the ACO algorithm.

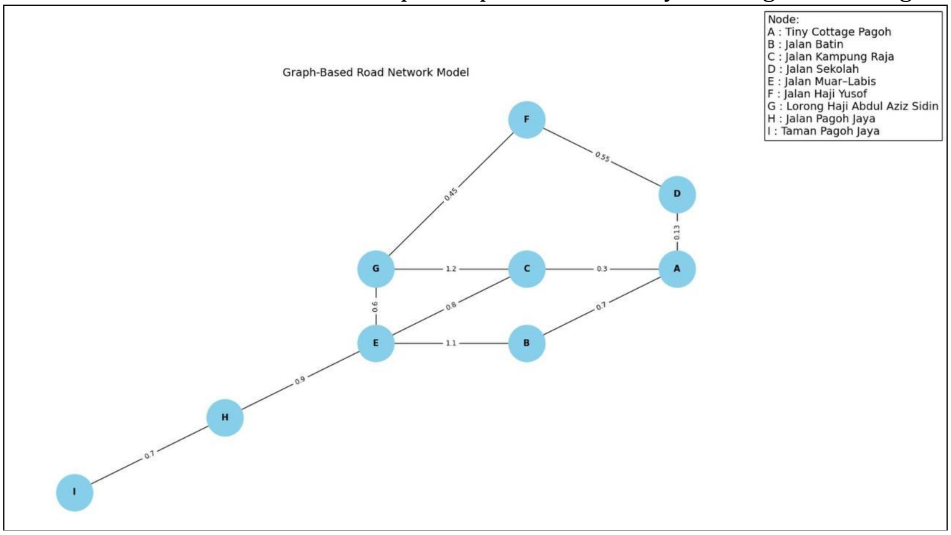

Fig. 1 Network graph of Pagoh

Fig. 1 illustrates the graph-based representation of the Pagoh road network. Nodes correspond to key locations and junctions, while edges represent the roads connecting them, weighted by distance in kilometres. The spatial arrangement of nodes approximates the general directional flow of the town, which aids visual interpretation of route connections. This network serves as the input structure for the ACO algorithm, enabling the simulation of multiple candidate routes between origin and destination points.

3.2 Optimal Route Identified Using ACO

The Ant Colony Optimization (ACO) algorithm was implemented to determine a short route from Tiny Cottage Pagoh (Node A) to Taman Pagoh Jaya (Node I) using the previously constructed weighted graph. At the beginning of the simulation, all artificial ants were initialized at Node A. During traversal, each ant selected its next node based on a probabilistic decision rule influenced by both pheromone intensity and heuristic information, where the heuristic value was defined as the inverse of the distance between two connected nodes [1], [2].

For each iteration, only ants that successfully reached the destination node contributed to pheromone updating. The total distance of each feasible route was calculated as the sum of the corresponding edge weights obtained from the distance matrix. Routes with shorter total distances received higher pheromone reinforcement, while longer routes received comparatively lower reinforcement, influencing the probability of route selection in subsequent iterations.

After several iterations, the algorithm converged to the route A → C → E → H → I, which exhibited a lower cumulative distance compared to other feasible routes in the network. Although alternative paths between Nodes A and I exist, these paths include either longer individual edge distances or a greater number of intermediate nodes, resulting in higher total travel distances.

The iterative nature of the algorithm allows a balance between exploration and exploitation. During the initial iterations, ants explored multiple candidate routes. As the simulation progressed, edges associated with shorter distances accumulated higher pheromone levels, increasing their selection probability [13]. In this study, edges A–C, C–E, E–H, and H–I consistently received higher pheromone reinforcement due to their shorter distances, guiding the algorithm toward convergence on this route.

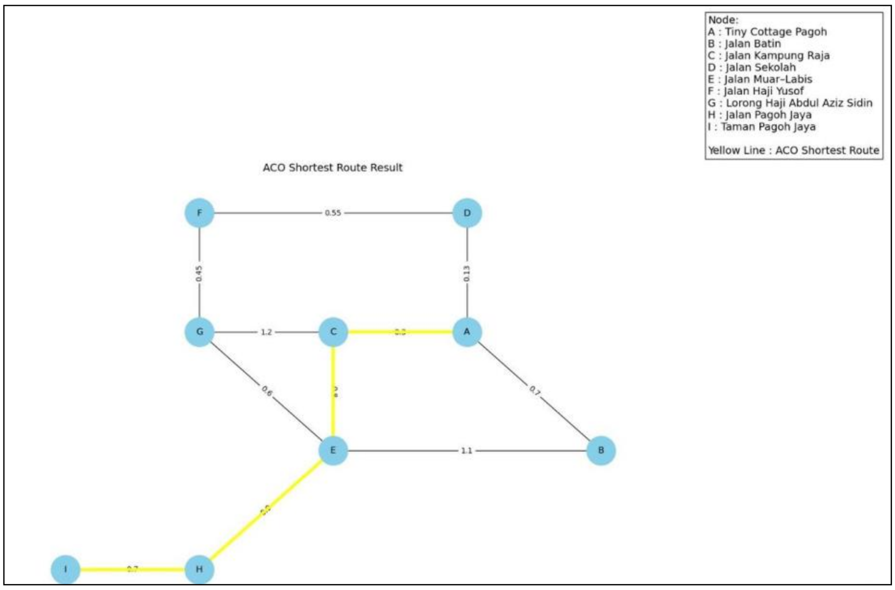

Fig. 2 Visualization of the shortest path from Tiny Cottage Pagoh to Taman Pagoh Jaya identified by the ACO algorithm. Nodes represent locations, edges represent roads, and edge weights correspond to distances in kilometres.

Fig. 2 illustrates the shortest route identified by the ACO algorithm from Tiny Cottage Pagoh to Taman Pagoh Jaya. Nodes represent key locations, while edges represent road connections with weights corresponding to distances in kilometres. The highlighted path corresponds to the sequence A → C → E → H → I.

Based on the simulation output, the distances along the selected route are 0.3 km (A–C), 0.8 km (C–E), 0.9 km (E–H), and 0.7 km (H–I), resulting in a total travel distance of 2.7 km. The consistency between the computed result and the weighted graph structure indicates that the algorithm was implemented correctly for the defined network.

Overall, the results suggest that ACO can be applied as a systematic approach for identifying short routes in a simplified town-scale road network. However, the findings are limited to the selected nodes and do not account for dynamic factors such as traffic conditions.

4. Conclusion

This study demonstrates that the road network of Pagoh can be effectively modelled as a weighted graph, where locations are represented as nodes and road connections as edges with associated distances. The graph-based modelling accurately represents the selected study area using actual road layouts and distance measurements.

The implementation of the Ant Colony Optimization (ACO) algorithm successfully identified the shortest path within the network. For the selected nodes, the optimal route from Tiny Cottage Pagoh to Taman Pagoh Jaya was determined as Tiny Cottage Pagoh → Jalan Kampung Raja → Jalan Muar–Labis → Jalan Pagoh Jaya → Taman Pagoh Jaya, with a total distance of 2.70 km. The consistency between the ACO output and the network distances confirms the correctness of both the graph formulation and algorithm implementation.

Although the network in this study is relatively small and the shortest path could be observed visually, the application of ACO provides a systematic and automated approach to route selection. This demonstrates the potential of optimization techniques for solving shortest path problems, even in simple network settings. The findings are limited to the selected nodes and routes within Pagoh but may serve as a reference for future studies involving larger or more complex road networks.

5. Recommendation

For future work, the network model of Pagoh can be further refined by incorporating additional locations and alternative routes within the town. Expanding the number of nodes and connections would allow the road network representation to better reflect real-world conditions and provide a more comprehensive evaluation of the Ant Colony Optimization (ACO) algorithm in practical routing scenarios.

In addition, future studies may consider including other influencing factors in the routing simulation, such as travel time or road congestion. Incorporating these factors would allow the optimization process to move beyond distance-based evaluation and provide a more realistic assessment of route efficiency under varying conditions.

Finally, the performance of the ACO algorithm can be further examined by comparing it with other well-established routing algorithms, such as Dijkstra's algorithm or Genetic Algorithms. Such comparative analysis would provide deeper insights into the strengths and limitations of ACO when applied to shortest route problems in graph-based road networks.

Acknowledgement

This research was supported by Universiti Tun Hussein Onn Malaysia (UTHM). The authors would like to express their sincere appreciation to UTHM for the support provided in completing this study.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design****: Nur Nadhirah Mohd Ripi, Muhamad Ghazali Kamardan;* ***data collection****: Nur Nadhirah Mohd Ripi;* ***analysis and interpretation of results****: Nur Nadhirah Mohd Ripi, Muhamad Ghazali Kamardan****; draft manuscript preparation****: Nur Nadhirah Mohd Ripi. All authors reviewed the results and approved the final version of the manuscript.*

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