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Influence of Shortest Route Approximation on Relegating Urban Area's Transportation Network Priorities

Pengaruh Pendekatan Laluan Terpendek ke Atas Menetapkan Keutamaan Rangkaian Pengangkutan Kawasan Bandar

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ABSTRACT

Vehicle routing instances designed for a proficient distribution network strategizing at maximizing traversal coverage had been consistently investigated for resolving dominant logistics scheduling issues involving cost reduction characteristics aside from emulating optimal travel patterns for minimizing possible traveling ranges while maximizing resource allocations. The purpose of this research is to highlight the incorporation of shortest path routing heuristics for maximizing traversable nodes of a round trip distribution cycle, to stretch the qualities of sentient pathfinding capabilities from prominent intelligent graph traversal algorithm specimens to produce prudent output in terms of addressing cost optimality constraints. This greedy pathfinding algorithm is regarded as proactive for application in several known neighboring routing characteristics, including customer clustering aspects in vehicle routing and location-allocation instances for optimal resource allocation.

Keywords**:** Shortest path, route optimization, A* algorithm, Dijkstra's algorithm, distance approximation

ABSTRAK

Keadaan pengangkutan kenderaan yang direka untuk strategi rangkaian pengedaran yang cekap dalam memaksimumkan liputan laluan telah selalu diselidiki untuk menyelesaikan isu-isu jadual logistik dominan yang melibatkan ciri-ciri pengurangan kos selain daripada meniru corak perjalanan optimal untuk meminimumkan julat perjalanan yang mungkin sambil memaksimumkan peruntukan sumber. Tujuan penyelidikan ini adalah untuk menonjolkan penggabungan heuristik laluan terpendek untuk memaksimumkan nod yang boleh dilalui dalam satu pusingan kitaran pengedaran, untuk meluaskan kualiti-kualiti kemampuan penemuan laluan daripada contoh algoritma laluan graf bijak yang terkenal untuk menghasilkan output yang berkualiti dalam menangani keperluan optimum kos. Algoritma penemuan laluan yang rakus ini dianggap proaktif untuk digunakan dalam beberapa ciri-ciri laluan bersebelahan yang dikenali, termasuk aspek pengkelasan pelanggan dalam pengangkutan kenderaan dan keadaan penentuan lokasi untuk peruntukan sumber optimum.

Kata kunci: Laluan terpendek, pengoptimuman laluan, algoritma A*, algoritma Dijkstra, anggaran jarak

INTRODUCTION

To set delivery priorities for different demand sectors, transport networks must plan routing variables, aggregate feasible transport, account for sufficient capacity, and set coverage priorities. Reducing unnecessary route diversions and promoting cost optimization is essential for a successful delivery network. Routing optimization studies show that priority delivery points are naturally selected to minimize operational costs. The shortest routes with multiple crossings can be combined to improve cost optimization. To avoid repulsive route deviations, strategic transit routes need to be identified to optimize cost allocation. Previous research has emphasized that the natural selection of priority distribution points reduces vehicle requirements and eliminates significant operating costs. By predetermining distribution priorities, clustering customer groups by distribution points improves task allocation methods. For example, intelligent pathfinding algorithms are computational intelligence applications that predict the shortest feasible travel routes. This reduces vehicle utilization and facilitates cost savings in the process. Furthermore, by grouping customer groups, the advanced routing optimization algorithm guarantees the right distribution points, optimizes efficiency, and reduces waste. Accurate route planning can improve customer satisfaction by reducing delays. Furthermore, better route optimization is expected to reduce fuel consumption and emissions. Consequently, current research trends on route optimization approaches seek to instill important routing characteristics to improve efficiency, whether it is operational costs or resource allocation to specific sectors. Shortest route heuristic algorithms are being developed to incorporate this approach into the logistics and transportation industry, leading to increased efficiency, better customer service, and better fleet management.

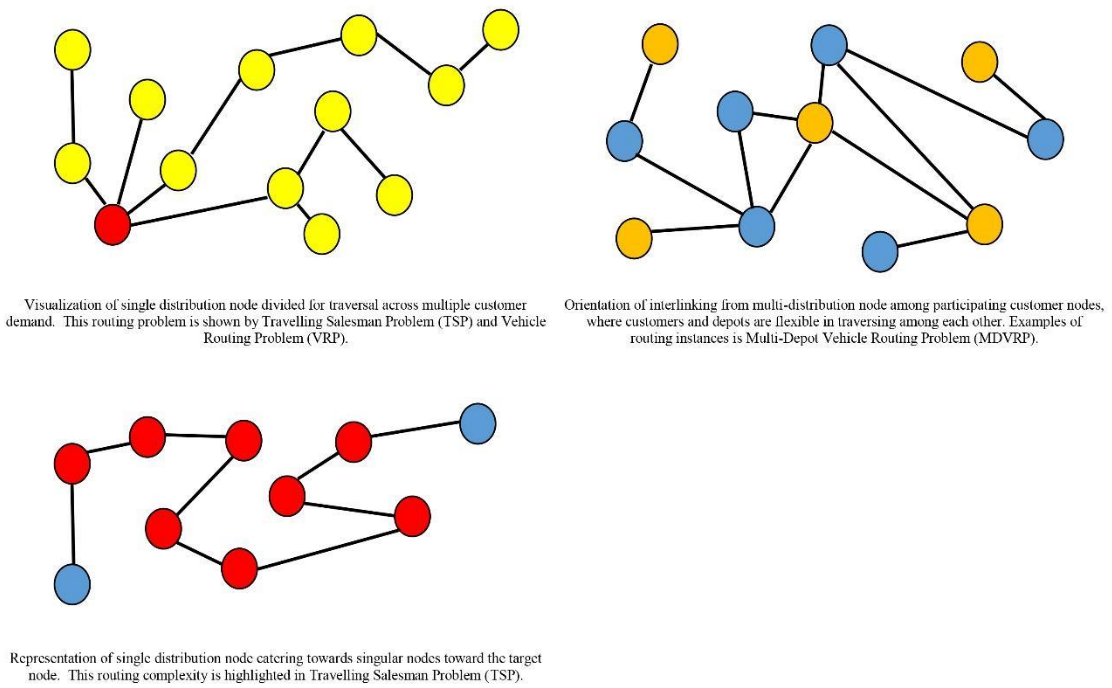


FIGURE 1. Variation of vehicle scheduling problems involving single and multi-distribution nodes

Myriads of routing strategies have been incorporated for addressing niche problems related to population density, maximum permissible coverage distance, and minimal time allotment for successful task deployment, apart from maximal load capacity for proactive freight distribution strategy. The relevance of identifying shortest path distance had been a continuous discussion topic among prominent routing strategies to date, and the benefits of improvising them for addressing singular Travelling Salesman Problem (Pinto, Quadros, Rathod, & Mittal 2020) or multiple objective accommodations such as Multi-Depot Vehicle Routing Problem (Chen, Lv, Ning, & Wu 2023) have been in many different implementations with similar motivations for promoting cost optimality.

PROBLEM STATEMENT

Finding the shortest path for a road network had turned into a critical component for constructing pathfinding applications. The fundamental goal of these implementations is to anticipate the best-expected travel path for common purposes such as commodities distribution and drive guiding system, as well as to give the most options for carrying out responsibilities while operating at the lowest feasible operational cost. Transportation system implementation studies use the shortest path issue solution technique to aggregate a better representation of distribution systems, aiding in the establishment of suitable distribution planning and deployment stages. The following are some of the frequent issues encountered in efforts to address the shortest path problem in transportation networks:

Identifying and simulating the best pathfinding approach for interconnecting linked places on a population cluster with various distance values

The distance between the customer's vehicle and the warehouse where the requisition order is delivered determines the deployment period. Estimates in the appropriate industries with strongly controlled commodities rules may be confusing due to issues such as redundancy when attempting to supply to several customers at once on the same route and inadequate infrastructure, such as broken roads and inaccessible depots. In industries with highly regulated route requirements, factors such as redundancy and poor infrastructure might lead to confusing estimations (Sularno, Mulya, Astri, & Mulya 2021). Sector prioritization is difficult due to fluctuating population concentrations and closeness to distribution centers. Because of changing population density and proximity to distribution centers, it is difficult to prioritize sectors. This issue could be remedied should routing models are structured towards the incorporation of sentient pathfinding capabilities that aggregated the shortest path to maximize the allocation of operating resources. The shortest path problem is a routing approach used in mapping applications to find the quickest way to connect two trajectory locations on a single road network hypothesis. Participants in a distribution network, such as customers and pick-up points, are represented in a graph quandary, consisting of vertices and edges with actual real-world values that determine relative positioning and distance between each node, using the approximation of the shortest path on mapping geological topographies.

Creating an efficient routing heuristic to reduce trip mileage and transportation costs

Certain routing model objective functions, such as avoiding cost waste and maximizing vehicle disposition across the participating distribution network, could be further optimized for a routing system architecture by simulating route trips using the shortest path heuristic between two vertices. The purpose of distribution network route optimization is to strike a balance between urban and rural accessibility. Annotating distribution points between prospect groups enables work scheduling to use suitable distribution chain patterns. During deployment, route closeness and accessibility must be considered when developing and scheduling an integrated transportation network that combines all important nodes into a systematic transport service across all sectors of interest. For proactive planning, real-world variables can be employed during correlation to suit the pattern of a planned scenario pattern.

Explain the significance of annotating the shortest path traveled along a distribution network in terms of enhancing overall routing optimality

The primary challenge in resolving the shortest path problem in routing instances is its consistency in handling the most critical component of vehicle scheduling, which is the location-allocation problems. In cases where routing capacities involve different population densities and demand area priority segregations, approximating shortest path designation among participating customers and pick-up points is critical for a smooth and uninterrupted routine distribution of supplies to be transported among the necessitating regions. This requires systematic road networks, integrated interdependent transport networks, and critical path networks (Sun, Li, Wang, & Xue 2022). Open urban design is essential for highly populated areas with well-organized growth because there are requirements for systematic road networks, integrated interdependent transit networks, and critical path networks. In high-availability zones, different degrees of strategic distribution point allocation must be handled. Cities are more likely to produce hotspot clustering for crucial distribution points within a road network due to their high population density. Annotating distribution points between prospect groups provide appropriate distribution chain patterns for task scheduling (Ochelska-Mierzejewska, Poniszewska-Marańda, & Marańda 2021).

RELATED WORK

With the cases of cost optimality, shortest path heuristics have been associated with myriads of cost reduction characteristics imposed for routing models. Among these features include customer clustering, greedy local search, and Travelling Salesman Problem. Although the shortest path problem based on graph theory represents a single-pair shortest path problem which is the conventional location-allocation problem incorporating all vertices from the source vertex in a graph was experimented on several occasions and proved its relevance, the proposal of a more efficient but robust algorithm has been constantly explored and incorporated in popular vehicle routing problems, for example, multi-depot and capacitated VRP. Therefore, several novel shortest path graph pathing algorithms such as Dijkstra and A* have seen their potential to be incorporated with niche routing simulations for addressing routing issues and remain important over the years among their counterparts.

In terms of estimating total distance coverage within a round trip, there could exist a discrepancy in location-allocation leading to the subpar allocation of operating costs (Sularno et al. 2021). Urban areas are more likely than remote places with dispersed populations to experience outbreaks of hotspots because of their high population density. The accessibility between urban and rural areas is balanced as a result of route optimization. Annotating the total distance achievable within a deployment period takes into account the distance between the transporting vehicle, participating customers, and the depot in which transits are done for fulfilling demand orders. Several ambiguous factors could reduce the estimation accuracy of advanced commodity regulation for the participating sectors, for example, redundancy of distribution attempts for multiple customers within a single route and faulty infrastructures such as broken roads and inaccessible depots (Sularno et al. 2021). Non-optimized scheduling arrangements would dampen the approximation of the initial estimated operating cost and influence the final operating expenditure as well, leading to subpar cost optimality. Different distribution channels need information on travel distances and potential customers. In this

way, transport networks can be optimized. Route proximity and accessibility inputs must be considered when planning and scheduling in an integrated transportation network that connects all relevant nodes into a systematic transport service across all sectors of interest during deployment, as these inputs form the basis for task assignment.
When it comes to the deployment of vehicles in high-availability regions such as cities and states, it is important to note that different levels of strategic allocation of distribution points need to be taken into account. Different population density and their reach with the adjacent distribution centers made it difficult to designate corresponding priority sectors reflecting an organized routing arrangement (Nuzzolo, Persia, & Polimeni 2018; Yu, Jodiawan, & Redi 2022). Diversified urban planning is strategized in heavily populated areas with thriving and organized development, for example, the imposition of the systemized road network and responsive interdependent transportation infrastructures along with the establishment of more accessible residential areas interlinking among the critical pathways (Sun et al. 2022). There is a varying degree in the allocation of strategic distribution points that were involved in vehicle deployment for areas with higher accessibility rates such as cities and prefectures as compared with rural communities that are less developed and less accessible in terms of interjecting road networks (Nuzzolo et al. 2018; Yu et al. 2022). Urban areas are susceptible to more access points due to their centralized population spread as compared with rural prefectures with scattered population density. There exists an imbalance when interlinking associated customer clusters with their distribution nodes for interjecting route optimization features among the urban and rural areas in particular due to accessibility. Therefore, it is crucial to establish a better annotation of distribution points among its potential customer clusters to properly reflect strategic distribution chain patterns to maximize the efficacy of any scheduling tasks (Ochelska-Mierzejewska et al. 2021).

Uneven distribution routes need to be supplemented with feed input regarding traversable distance and the number of available customers to establish a transportation network with sufficient credentials for optimizing cost estimations. To establish an integrated transportation network connecting all associated nodes for systemized transportation of services across all participating sectors during deployment instances, feed input regarding route proximity and accessibility needs to be assimilated into the planning and scheduling of task distribution fundamentals so that a better-generalized representation of traversal link could be established. Feed data inclusive of the total distance between 2 points, linkable sections among the node components, and corresponding distance between vertex and edges along a convergence line, and limits on accessibility among corresponding regions need to be incorporated for a proactive subjugation of scheduling variables with its interoperability for actual scheduling route scenario patterns (Sun et al. 2022). Real-world variables can be used during correlation to match the pattern of a planning scenario pattern for a more proactive planning variable, including distances between nodes, link sections between nodes, edges along convergence lines, and entry limits between corresponding areas (Sun et al. 2022).

EXPERIMENTAL DEMOGRAPHY

An emulation of the food distribution network is created from the actual distances and locations of the main supermarkets in Sibu, Sarawak. These destination nodes are converted into a non-negative weighted graph representation with vertices and edges representing the starting position and the separation between the destination nodes and between two interconnected nodes. A scripting tool is programmed in Java to generate the overall transportation network model and visualize the waypoints, and the comparability of the shortest distance progress completed between the basic A* algorithm implementation and the proposed shortest path heuristic is evaluated for similar problem instances. The performance of the system is measured from the extended range of nodes along with the sum of the cumulative distances of both path heuristics compared.

SHORTEST PATH TRAVERSAL HEURISTICS

The shortest path approximation method emulates minimal traversal routes in distribution networks using pathing algorithms. The optimal shortest path is determined by summarizing the travel route with the least distance from participating vertices. Routing solution strategies are optimized through region division and localized initial solutions, enhancing depot pickup and optimizing logistic facility and transport deployment. The concept of this method is motivated by the goal to minimize logistic costs along with vehicles deployed and can be incorporated into aggregating customer clusters relative to depots to maximize distribution satisfaction and obtain a distinct travel pattern for future reference (Luo, Wang, Tang, Guan, & Xu 2021).

i. A* PATHING ALGORITHM

The A* algorithm is a heuristic estimation method for forecasting that approximates the most optimal path-splitting strategy. The executed pathing mechanism prioritizes routes with the least recurring costs based on a weighted graph and is superior to blind search algorithms (Wang et al. 2022). The path with the lowest cost is chosen in local optimization by evaluating neighboring node costs and selecting the path with the lowest cost tendency. The search continues until no unused nodes are found. The A* pathfinding procedure adheres to heuristic criteria assimilation, aggregating subsequent traversals based on route characteristics and iterating constantly until the termination criterion is met (Foead, Ghifari, Kusuma, Hanafiah, & Gunawan 2021; Wang et al. 2022). The fundamental underworking of the incurred steps is discussed as follows.

Execution criteria

1. Add the beginning location to the open list and empty the closed list during initialization.
2. While there are more probable next steps on the open list and the destination node has not been found:
   i. *Based on the heuristic and path costs, choose the most likely next step.*
   ii. *Remove from the open list and move to the closed list.*
   iii. *Identify and process each step's neighboring nodes.*
3. Determine the cost of reaching the neighbor. For each neighbor node iteration:
   i. *If the cost is less than the known cost for this site, it should be removed from the open or closed lists because a better route has been discovered.*
   ii. *If the location is not on the open or closed list, record the charges and add them to the open list for consideration in the future search.*
4. Loop steps 2-3 until the destination node is achieved.

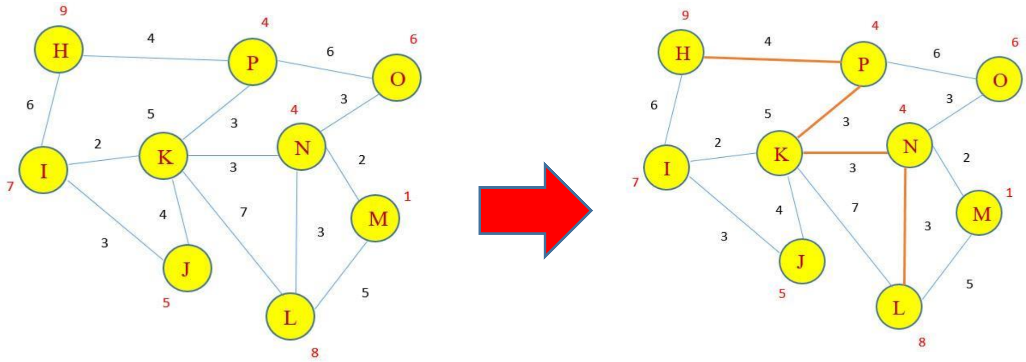


FIGURE 2. Route Selection using A* Pathfinding Features

Figure 2 shows the procedures for obtaining the estimated shortest path between the chosen starting and destination nodes. Heuristic knowledge involving vertex and edge connections is applied using the concepts of A* pathfinding as a goal-directed method to identify priority nodes that are allegedly better composed than others and to try and reduce any inherent distances projected in the traversal network. After accounting for each shortest path that is involved in the trade-off, the devised optimized route, which originates at node H, is determined to be H-P-K-N-L (4+3+3+3=13).

TABLE 1. Pseudocode for the Applied A* Algorithm

1:	**Construct**
	An open list containing only the original vertices
	Empty closed list
2:	**If**
	The target vertex has not been reached
3:	Insert the vertex with the lowest *f* score into the open list
4:	**If**
	Current vertex = target vertex
5:	**Stop**
6:	**Else**
	Insert the current vertex in the closed list queue
	Compare with all currently available neighboring nodes
7:	**For**
	Each neighboring vertex of the current vertex
8:	**If**
	The value of the neighboring vertex <*g* of the current vertex
	Place neighbor in the closed list
9:	Replaces the neighbor with the last smallest *g* value
10:	Current vertex = parent of the neighboring vertex
11:	**Else if**
	The current *g* is low
	Neighbors are listed in the open list
12:	Replaces the neighbor with the last smallest *g* value
13:	Current vertex = parent of the neighbor
14:	**Else if**
	The neighbor does not exist in both lists
15:	Add to open list and define as *g*
	END

ii. PROPOSED GREEDY DIJKSTRA WITH HAVERSINE METRIC

The shortest distance between two edges in a weighted graph is assumed to be straight-line propagation, but it is unlikely to be represented in real mapping scenarios. Challenges exist in finding the lowest-cost path between 23 vertices without relying on weighted graph assumptions, especially for non-symmetric geographical locations near traversable routes. This method combines alternative selection strategies for identifying minimized constituent edges in single-pair shortest path problems in graphing networks (Talan, Karishma; Bamnote 2015; Yuliani, Rozahi Istambul, & Angga Laksana 2021). Road networks are emulated as vertex and edges as intersections and segments. The shortest path heuristic uses Dijkstra and Haversine metric concepts to formulate a tree structure with the best passable alternatives of node traversal (Alam & Faruq 2019; Rachmawati & Gustin 2020; Sularno et al. 2021; Wayahdi, Ginting, & Syahputra 2021). The algorithm gradually increments fixed distance values, with the current intersection marked as a not-visited point. The distance sum for non-traversed intersections is updated if it is less than the current value, and the current intersection is marked as visited. A prohibition on repeated traversal is imposed on the visited vertex. The fundamental concept of interlinking neighboring distance is promoted through the combination of the proposed technique and comprehensive traversal, ensuring the shortest possible distances are accumulated. The process is summarized as follows.

Execution criteria

1. Except for the starting point, all points should have their distances set to infinity.
2. The starting point and all other points are both set to be non-visited nodes.
3. The non-visited node exhibiting the smallest current distance is designated as the current node.
4. The edge weight connecting the current node neighbors is added. If the distance to be traversed from the subsequent node is shorter than the current distance, that distance is applied as the new distance.
5. The current node is marked as visited.
6. The process is repeated (steps 3-5) until the destination node is achieved.

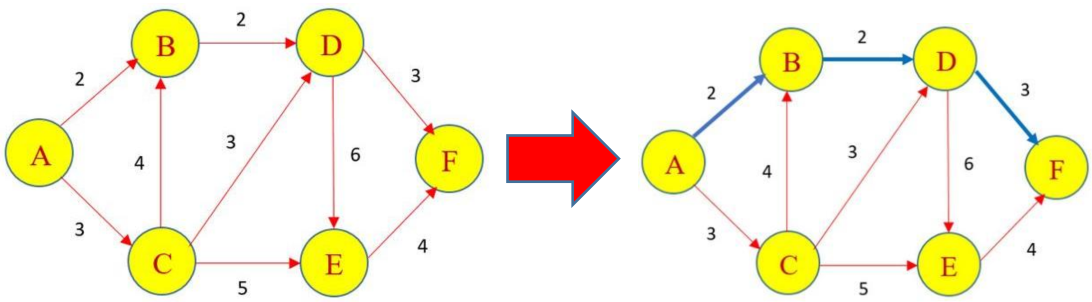


FIGURE 3. Route Selection using the Proposed Shortest Path Heuristic

The proposed pathfinding heuristic combines Dijkstra and BFS node branching traits, representing distances between nodes and fixed positioning for each node. These predecessor values are traversed to find the shortest path to all nodes. The relaxation technique is preferred for optimal traversal, choosing the predecessor node with the smallest distance to be aggregated with the current destination node. The path through the lowest-valued vertex, including A-B (2), B-D (2), and D-F (3) = 7, is found to be the best traversal path. The solution strategy considers the maximum number of nodes reached in a single round trip and the completion time the shortest path takes.

TABLE 2. Pseudocode for the Shortest Path Heuristics based on Dijkstra & BFS

```
1:    Construct:
      nodes with infinite distance, initialization of starting node = 0
2:    For each
          Vertex, v
3:        distance[v] : infinity
          previous[v] : undefined
4:    distance[source] = 0
5:    Q = Set of all nodes in the graph
6:    While
          Q is not null
7:            u: Node in Q with the smallest distance
              remove u from Q
8:        For each
              Neighbour v of u
9:            alternate: distance[u] + distance_between (u, v)
10:           If
              alternate: distance[u] + distance_between (u, v)
11:           If
              alternate < distance [v]
12:               distance [v] = alternate
                  previous [v] = u
13:   return
14:       previous []
        END
```

DISTANCE APPROXIMATION METRIC

Conventional distance metrics such as Euclidean and Manhattan calculations are useful for computing unidirectional path traversals on weighted graphs, but not ideal for combining curved roads into linear edges for routing distance approximation. This experimental study uses the Haversine distance metric to estimate the surface distance of routes on weighted graphs with non-negative edges. It is combined with a path algorithm using a location identifier derived from latitude and longitude. The algorithm calculates the shortest distance on a round trip by accounting for nearby nodes and the shortest distance. The heuristic is applied with presumptions such as a symmetrical network, an end-to-end route without duplication or return, and predetermined depot and customer locations. The fundamental notation for Haversine is as follows:

$$haversine(\theta) = sin^2 \frac{\theta}{2} \quad (1)$$

Assumption: Radius of earth's surface = 6371km

$$\mathrm{a} = \sin^2\left(\frac{\varphi B - \varphi A}{2}\right) + \cos \varphi\mathrm{A} * \cos \varphi\mathrm{B} * \sin^{22}\left(\frac{\lambda B - \lambda A}{2}\right) \quad (2)$$

$$\mathrm{c} = 2 * \mathrm{atan2}\ (\sqrt{\mathrm{a}}, \sqrt{(1-\mathrm{a})}) \quad (3)$$

$$\mathrm{d} = \mathrm{R} \cdot \mathrm{c} \quad (4)$$

Where:
φ = latitude, λ = longitude, and R = Earth's radius (6371 km)

PROBLEM CHARACTERISTICS

The shortest route heuristic is simulated for distribution supply among 23 supermarket chains in Sibu, with a starting point at Sibu Central Market. These supermarkets act as pick-up points and interlink among their closest partnering nodes. The traversal process is a one-way cycle, with backtracking omitted. Figure 4 shows the workflow of the proposed shortest route approximation heuristic iteration, while Figure 5 shows the real-world mapping of the intended destination node for the proposed shortest pathing heuristic.

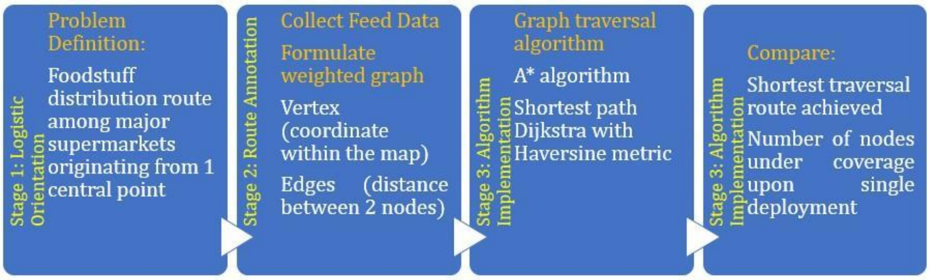


FIGURE 4. Framework for the Proposed Shortest Route Heuristic

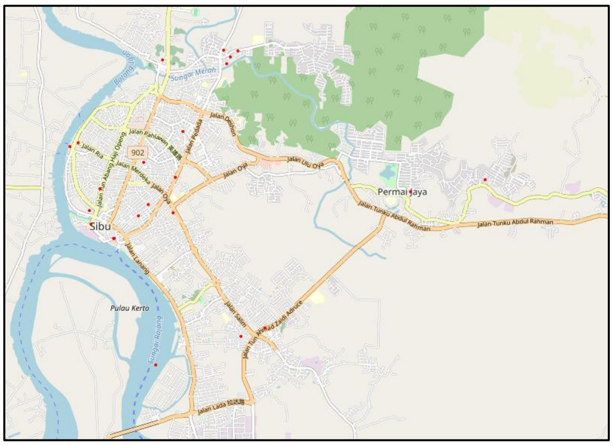


FIGURE 5. Geographic demography of the 23 supply chains around Sibu, Sarawak

TABLE 3. Coordinates Representing the Participating Foodstuff Distributors

Node	Coordinates (x, y)	The interval from the initial node (km)
Bataras	2.29295, 111.83435	1.2
Bisonte	2.30952, 111.82063	3.2
CCL Fresh	2.30112, 111.91330	12.4
Central Market	2.28764, 111.82873	0
Delta	2.31209, 111.84447	5.1
Doremart	2.32842, 111.83981	5.7
Doremart2	2.29550, 111.83664	1.3
Eco Fresh	2.33049, 111.85705	7.5
Everwin	2.32750, 111.85441	6.0
Everwin2	2.29098, 111.82364	0.6
Fair Price	2.29410, 111.82318	1.1
Family	2.33059,111.85370	6.6
Farley	2.26733, 111.86326	6.7
G-Mart	2.29829, 111.89631	9.5
JumboXpress	2.28767, 111.82895	0.3

Kim Hock	2.30163, 111.84276	3.0
MDS	2.30866, 111.81881	3.1
Medan	2.29351, 111.84233	1.9
Medan (Li Hua)	2.258953,111.838339 6	4.9
Rega	2.30503, 111.83561	4.3
Sing Kwong	2.29901, 111.82561	1.5
Sing Kwong2	2.26542, 111.85772	5.7
Wonderful	2.32903, 111.85541	7.6

RESULT AND DISCUSSION

This section investigates the proposed shortest path approximation heuristic's performance on round-trip traversal for distribution purposes. From a list of significant food distributor locations, five nodes with the greatest distance from the beginning point are chosen. The goal is to compare the efficiency of both heuristics in expanding to the most nodes while meeting the journey target.

Performance variation in the compared pathing heuristics is shown in Table 4. The A* method outperforms the proposed routing heuristic in terms of computational speed. This tendency rises with route complexity since more traveled nodes are imposed during round trips. However, even when A* visits somewhat fewer nodes than the proposed heuristic, there is inconsistency in execution time relative to the number of traversed nodes. The suggested pathing technique exhibits consistency in incremental node disposition parallelism and execution time.

TABLE 4. Computational Speed for Both Compared Pathing Heuristics

Target Destination	Execution Time for Node Traversal (/sec)	
	A*	Proposed
CCL Fresh	37	53
Eco Fresh	12	21
Farley	35	43
G-Mart	23	44
Wonderful	40	41

TABLE 5. Results of round-trip simulation using the A* algorithm and the proposed heuristic

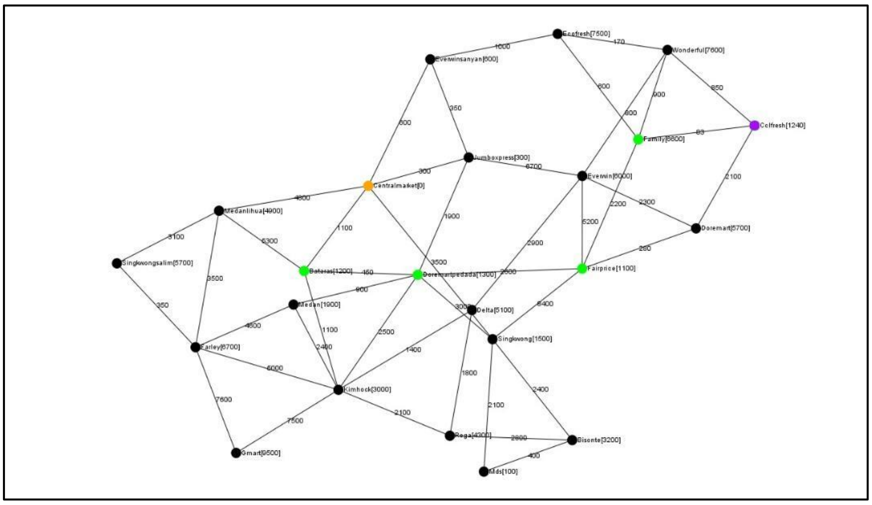
Target Destination	Total Distance (km)		Number of traversed nodes	
	A*	Proposed	A*	Proposed
CCL Fresh	6.95	8.15	5	7
Eco Fresh	8.10	7.47	2	7
Farley	7.10	7.20	5	4
G-Mart	10.3	9.70	3	4
Wonderful	8.27	7.30	7	6
Average	8.144	9.594	22	28

Both the A* method and the suggested pathfinding algorithm estimate the shortest paths to similar destinations. The A* algorithm, on the other hand, has a pathfinding fault in that it only finds the best nodes aligned in a straight line, which is impractical for practical applications with curved distances. The suggested pathfinding heuristic validates absolute annotated nodes and distances to nearby nodes more thoroughly, allowing for more realistic solution approximation. Under a multi-level tree structure, the proposed greedy pathfinding heuristic performs better in bidirectional searches with low traversal distances. The node with the most registered nodes and the least distance allocation is promoted to maximize route optimization by minimizing the trade-off between propagation distance and coverage area.

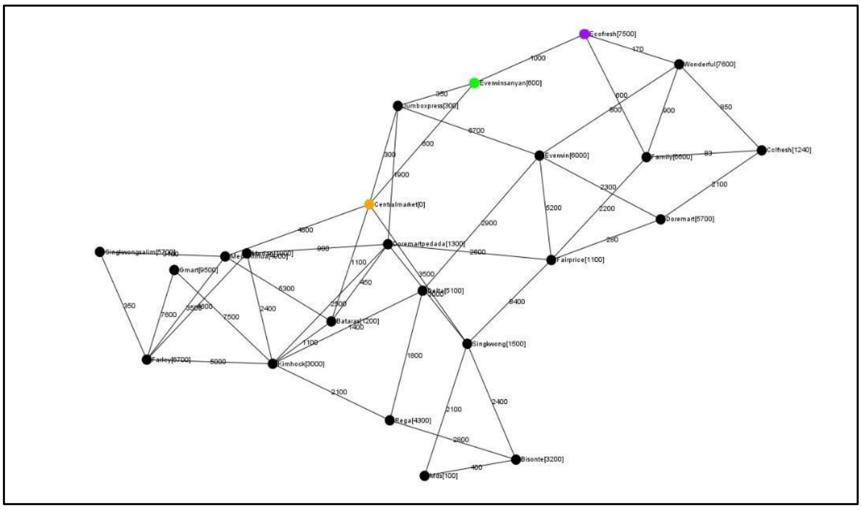
The dissipation of route optimization between two pathing approaches is shown in Table 6. The shortest path heuristic is consistent in terms of node expansions and traveling distance, however, the A* algorithm varies in terms of node dissipation and propagation. The suggested method subjectively traverses relative nodes to show the optimum alternative distance, allowing for a more thorough assessment of routing options while collecting the highest feasible distance coverage. The A* method, on the other hand, does not extend the heuristic function, resulting in a contradiction in complex traversal networks. The proposed pathing heuristic is better compatible when combined with appropriate graph weightage and structurally linear tree architecture. However, due to the loss of execution performance in more sophisticated networks, additional computing costs may be required. For relative cases, both strategies are separate, with A* for speedier solution discovery and the greedy pathfinding heuristic for in-depth node exploitation. Figures 6.1-6.2 show the A* and proposed pathing heuristics' performance. For both testing instances, the source node starts at Sibu Central Market (light brown), traversing through medium nodes (green = branch 1, blue = branch 2, red = branch 3), before ending at the target node (A* = purple, proposed = yellow).

TABLE 6. Comparison of traversed node distance using the A* algorithm and the proposed heuristic

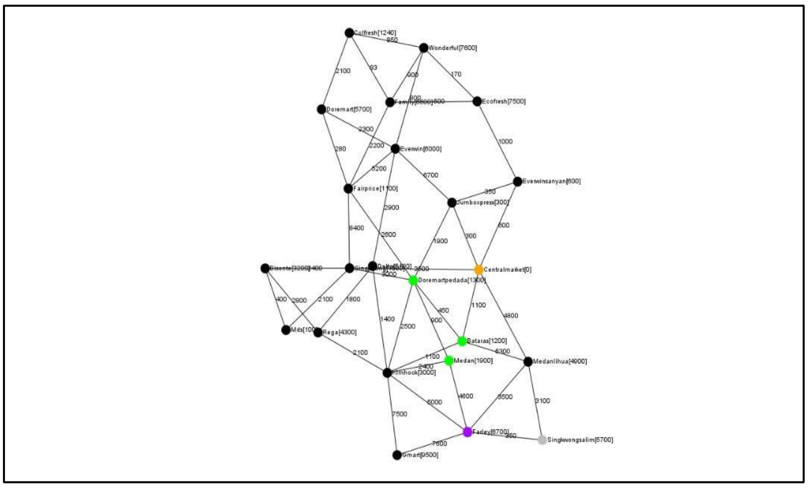
Target Destination	Node traversed during the deployment	
	A*	Proposed
CCL Fresh	Centralmarket (0.0 Km) <-- Bataras (1.1 Km) <-- Doremartpedada (1.55 Km) <-- Fairprice (4.15 Km) <-- Family (6.35 Km) <-- Cclfresh (6.95 Km)	Centralmarket (0.0 Km) -> Bataras (1.1 Km) -> Kimhock (2.2 Km) -> Delta (3.6 Km) -> Everwin (6.5 Km) -> Wonderful (7.3 Km) -> Cclfresh (8.15 Km)
Eco Fresh	Centralmarket (0.0 Km) <-- Everwinsanyan (0.75 Km) <-- Ecofresh (8.1 Km)	Centralmarket (0.0 Km) -> Bataras (1.1 Km) -> Kimhock (2.2 Km) -> Delta (3.6 Km) -> Everwin (6.5 Km) -> Wonderful (7.3 Km) -> Ecofresh (7.47 Km)
Farley	Centralmarket (0.0 Km) <-- Bataras (1.1 Km) <-- Doremartpedada (1.55 Km) <-- Medan (2.5 Km) <-- Farley (7.1 Km)	Centralmarket (0.0 Km) -> Bataras (1.1 Km) -> Kimhock (2.2 Km) -> Farley (7.2 Km)
G-Mart	Centralmarket (0.0 Km) <-- Bataras (1.1 Km) <-- Kimhock (2.8 Km) <-- Gmart (10.3 Km)	Centralmarket (0.0 Km) -> Bataras (1.1 Km) -> Kimhock (2.2 Km) -> Gmart (9.7 Km)
Wonderful	Centralmarket (0.0 Km) <-- Everwinsanyan (0.75 Km) <-- Ecofresh (8.1 Km) <-- Wonderful (8.27 Km)	Centralmarket (0.0 Km) -> Bataras (1.1 Km) -> Kimhock (2.2 Km) -> Delta (3.6 Km) -> Everwin (6.5 Km) -> Wonderful (7.3 Km)



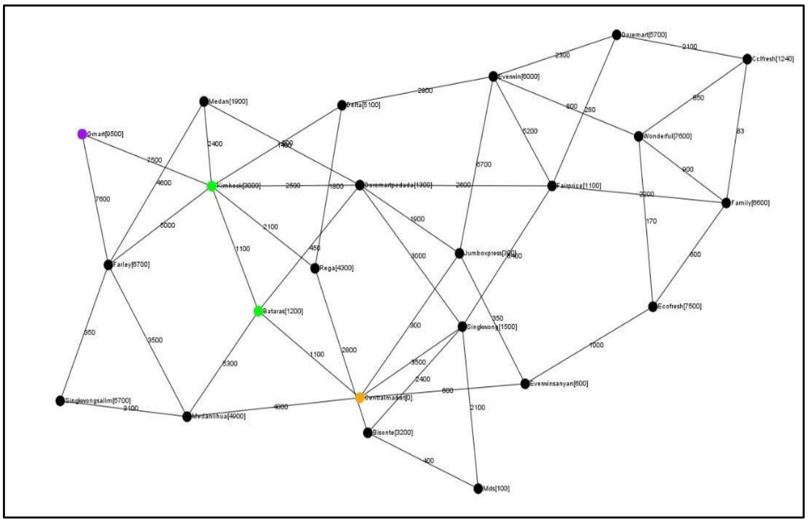
6.1 (a) CCL Fresh



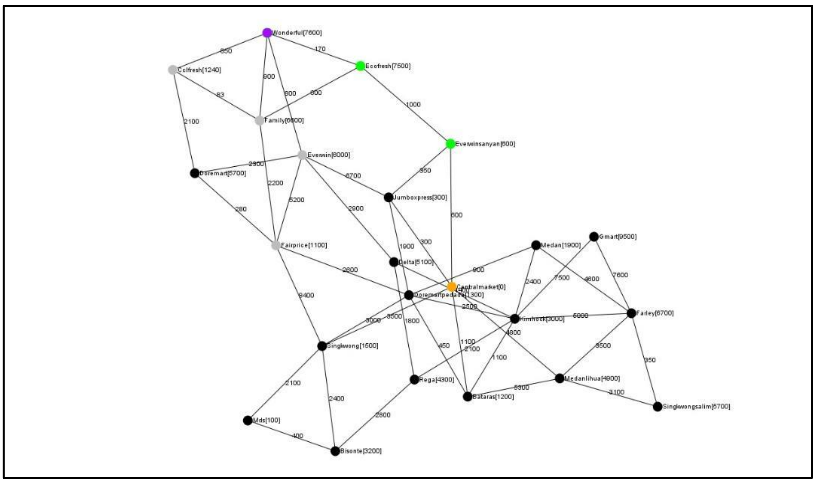
6.1 (b) Eco Fresh



6.1 (c) Farley

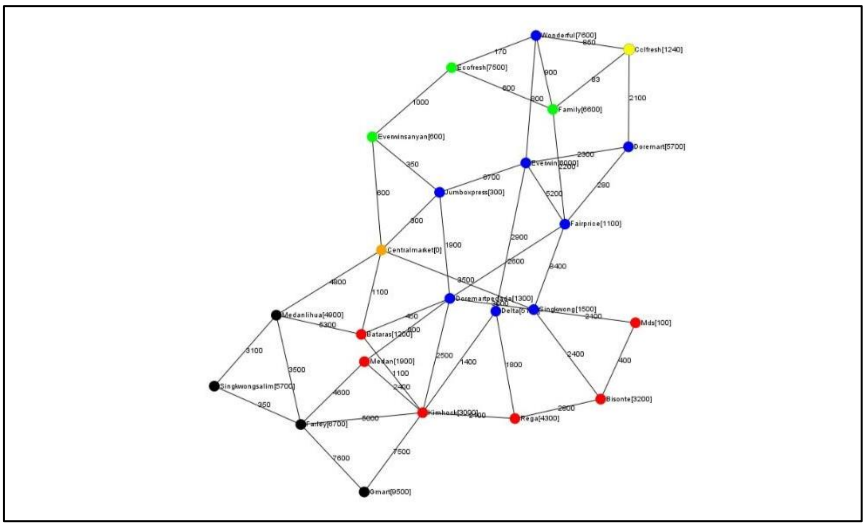


6.1 (d) G-Mart

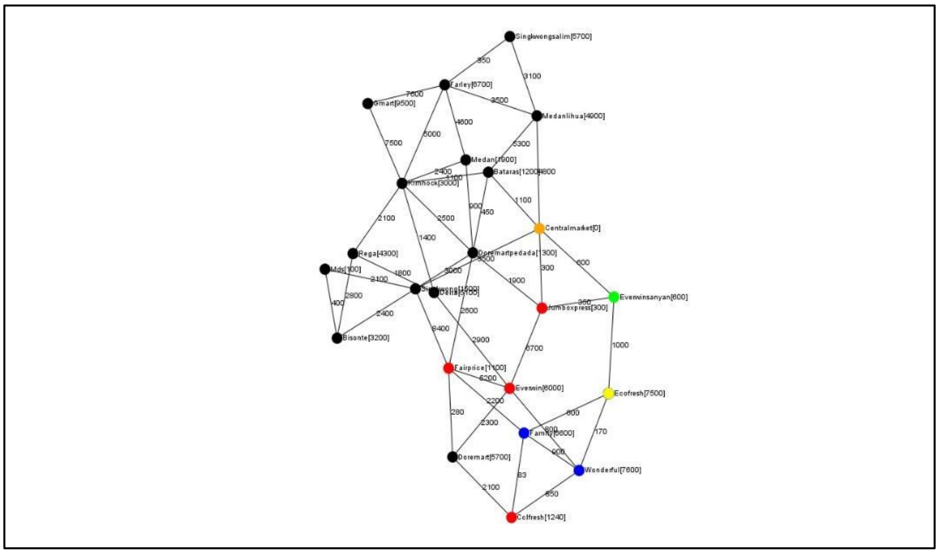


6.1 (e) Wonderful

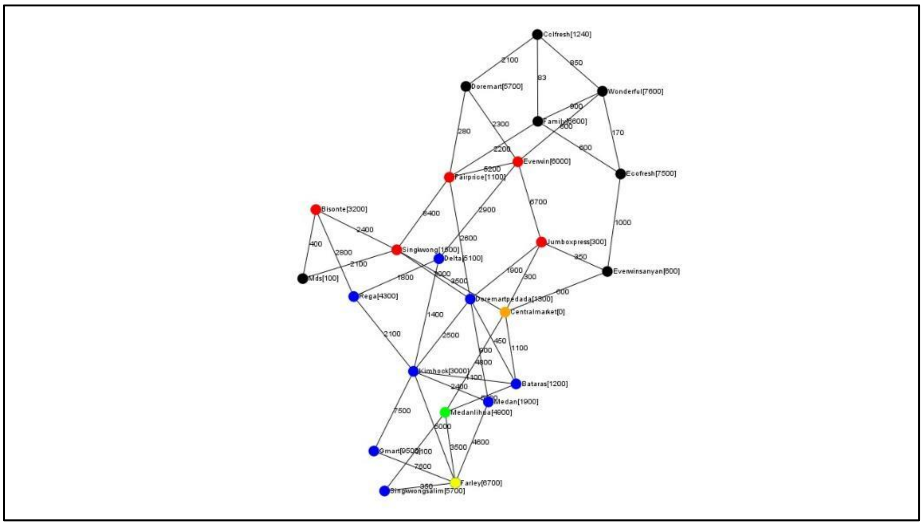
FIGURE 6.1 Results of the Route Traversal at Respective Nodes using A* Pathfinding Algorithm



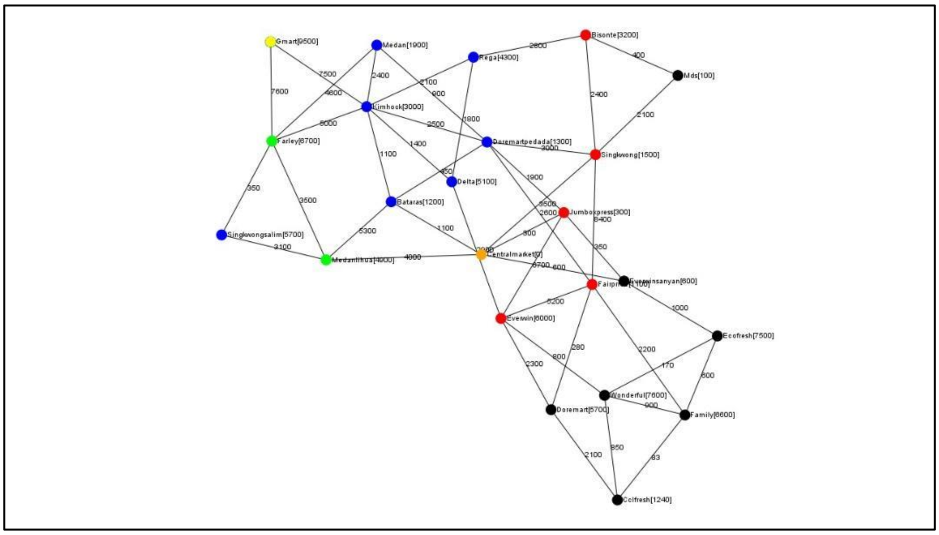
6.2 (a) CCL Fresh



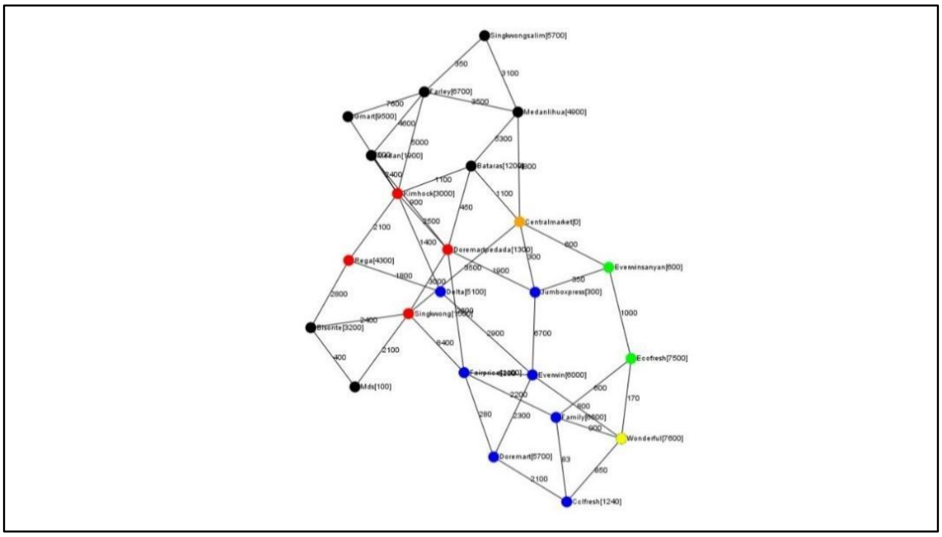
6.2 (b) Eco Fresh



6.2 (c) Farley



6.2 (d) G-Mart



6.2 (e) Wonderful

FIGURE 6.2. Results of the Route Traversal at Respective Nodes Using the Proposed Pathfinding Heuristic

Table 7 illustrates the result findings from the overall simulation of the comparison between the compared baseline A* pathfinding algorithm and the proposed greedy shortest path heuristic in incorporating the custom customer array among the designated key distribution destinations.

TABLE 7. Total Value of the Traversed Distance and Nodes based on the Tested Shortest Path Heuristics

Target Destination	Total Distance (/m)		Number of traversed nodes			
	A*	Proposed	A*	Time (sec)	Proposed	Time (sec)
Bataras	1200	1200	1	5	3	23
Bisonte	5900	3900	3	19	6	32
Delta	8700	9200	4	27	16	61
Doremart	4530	12000	5	33	14	62
Doremart2	1650	1650	2	20	8	45
Everwin	7000	6300	3	26	11	48
Everwin2	1200	2100	1	9	1	9
Fair Price	4250	2600	3	28	14	56
Family	6450	9700	5	38	10	44
JumboXpress	300	300	1	22	4	30
Kim Hock	4200	4200	2	21	14	54
MDS	3600	3600	3	19	4	24
Medan	3550	2750	3	24	13	62
Medan (Li Hua)	4900	4800	1	11	2	12
Rega	8500	6700	3	26	12	48
Sing Kwong	3500	1500	2	16	1	12
Sing Kwong2	7700	8000	5	35	4	21

The next Table 8 summarizes the highlight point for the execution of the 2 tested routing heuristics in estimating the shortest possible traversal path via the representation of distance nodes as an unweighted graph.

TABLE 8. Comparison of Traits between the 2 Tested Pathing Algorithms in Estimating Shortest Distance Metric

Characteristics	A*	Proposed Heuristic
Execution concept	Acquires the lowest-cost paths between participating nodes and the closest distance to the problem definition using additional heuristic knowledge	Propagation with node traversal exhibiting the lowest cost
Traversal optimization probability	Iterative toward the target solution	Capable to produce an optimal solution for weighted and unweighted graphs based on certain circumstances
Speed	Emphasizes the critical nodes and swifter due to the relatively smaller search tree	Speed gradually reduces with the complexity of the search tree
Expansion range	Targets only the closest node in relative with the problem definition, scours through neighboring node	Uniform contours spread through all directions until the solution is found
Exhibited computational cost	Requires less computational cost, but is not highly accurate and representative	Incremental execution cost, but more definitive and absolute in representing overall solution cost
Graph representative (weighted/non-weighted)	Only accommodate positive values	Non-negative input

CONCLUSION

This study explores the underlying rudimentary scheduling systems reflecting location-allocation concerns, with the goal of better optimizing feature representation for customer clustering inside distribution network cycles. The enhancement of shortest path approximation in supporting the identification and rapid planning of essential distribution nodes is considered as advantageous in increasing cost optimality and future deployment progress. This research's conceptualization is thought to be plausible for further investigation for implementation in major vehicle traversal-related fields of research, such as vehicle routing difficulties and logistic scheduling instances such as disaster logistics. Experiment results suggest that the heuristic can be used to optimize mapping routing and path planning efficiencies. Improvements in the routing scheduling aspects are seen as viable through the research implementation in terms of integrating supplementary feed data representing the road network for better path classification subjugation, and further collaborating with clustering methods to locate proper routes on a smaller and more compact scale.

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