A Comparative Analysis of Heuristic and Dynamic Algorithms for Route Optimization in Johor's Delivery Hubs

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ABSTRACT

Delivery route optimization is crucial for enhancing logistics efficiency and reducing operational costs in the e-commerce industry. During the COVID-19 pandemic, Movement Control Order (MCO) in Malaysia led to a surge in online shopping as physical stores were closed. This study focuses on optimizing delivery routes between J&T hubs in Johor using three algorithms: Dynamic Programming (DP), Genetic Algorithm (GA) and Simulated Annealing (SA). The objectives include employing these algorithms to determine optimal routes, considering both distance and time and comparing GA and SA against DP as a benchmark. Data from 18 delivery hubs were analyzed using Python, with distance and travel times from Google Maps. All three optimazation methods were successfully applied to determine the optimal delivery route. The results demonstrated that DP consistently provides optimal solutions and emerged as the most effective method. The ideal departure time for both weekdays and weekends was identified as 10 p.m., with 667 minutes for weekdays and 641 minutes for weekends, respectively.In the comparison between GA and SA, GA outperformed SA in 8 out of 9 cases. However, at 6 p.m. on a weekend, SA achieved a shorter duration of 720 minutes compared to GA's 742 minutes. These findings suggest that GA could be effectively adopted by logistics companies to optimize operations, reduce delivery times and meet the growing demands of e-commerce. Future applications could involve integrating real-time traffic data to further refine route optimization in dynamic environments. Additionally, hybrid approaches combining the strengths of DP, GA and SA could be explored to address complex logistics challenges in various regions, contributing to optimized delivery systems for congested urban areas, faster deliveries, and reduced the environmental impact.

Keywords: Delivery route, E-commerce industry, Dynamic Programming, Genetic Algorithm, Simulated Annealing

INTRODUCTION

During the COVID-19 pandemic, Malaysia experienced a shift from physical shopping to online purchasing due to government-imposed Movement Control Orders (MCO). Courier services became essential for facilitating logistics for e-commerce platforms, serving both small-scale vendors on platforms like Shopee and Lazada and large enterprises operating nationally and internationally [1]. Courier services offer a diverse range of options, including express same-day deliveries for urgent shipments, overnight services guaranteeing delivery within 24 hours, international logistics handling cross-border tariffs and taxes and standard services providing reliable, cost-effective solutions for everyday shipping. With features like tracking, door-to-door delivery and real-time updates, they ensure faster, safer and more reliable than traditional postal services. Although couriers come at a higher cost, this is justified by their advanced logistics and professionalism [2].

The growth of e-commerce in Malaysia has driven the expansion of the courier industry. Companies such as Pos Malaysia, J&T Express and DHL has expanded their operations to meet the growing demands for efficient delivery solutions [3]. Reliability, a key factor in courier services, ensures timely, accurate and damage-free deliveries, driving customer satisfaction, loyalty and operational efficiencies. In 2021, Malaysia's e-commerce transactions reached RM 1.09 trillion, a 21.8% increase from the previous year, creating challenges for courier companies to optimize delivery routes, ensure timely deliveries and meet customer expectations for reliable service [4].

Numerous studies have examined the impact of COVID-19 on e-commerce, highlighting significant shifts in consumer behavior during the pandemic. Bhatti et.al (2020) observed an increase in e-commerce frequency in the early months of the outbreak, driven by the need to minimize physical interactions and comply with safety protocols [5]. Similarly, Kawasaki et al. (2022) noted that consumers turned to e-commerce primarily to maintain social distancing [6]. These studies also suggest that the pandemic not only accelerated the adoption of online shopping but also reshaped shopping habits, with many consumers substituting trips to physical stores with online purchases. This shift was particularly evident during the initial waves of disease and lockdown periods, while e-commerce's role as a critical alternative for accessing goods and services during the infection.

This study focused on optimizing the delivery routes between hubs in Johor using advanced algorithms such dynamic programming, genetic algorithms and simulated annealing to identify the most efficient routes based on distance and time. These findings will provide valuable insights for improving courier service efficiency, reducing costs and enhancing customer satisfaction, ultimately supporting the growth of Malaysia's e-commerce industry.

MATERIALS AND METHODS

The data for the study was obtained from two main sources: the official J&T website and Google Maps. The delivery hub locations within Johor were sourced from the official J&T website. A total of 18 hubs were considered in the analysis. The distances between the hubs, measured in kilometers, were collected from Google Maps while the travel times between hubs, measured in minutes, were also collected from Google Maps. The study considered different traffic conditions during weekdays and weekends at four key time periods (8 a.m., 1 p.m., 6 p.m., and 10 p.m.).

Table 1 List of 18 delivery hubs in Johor

District	Hub Name	Hub Node
Pontian	Kukup	1
Johor Bahru	Nusa Bestari	2
	Pulai Mutiara	3
	Larkin	4
	Bukit Batu	5
	Kangkar Pulai	6
	Nusa Sentral	7
	Pasir Gudang	8
	Ulu Tiram	9
Kulai	Kulai	10
	Kelapa Sawit	11
Muar	Parit Jawa	12

	Pagoh	13
Tangkak	Tangkak	14
Batu Pahat	Penggaram	15
Mersing	Tenggaroh	16
Kluang	Taman Emas	17
Kota Tinggi	Desaru	18

The analysis was conducted using Python, a versatile programming language well-suited for data analysis and optimization tasks. The implementation of the algorithms utilized Python's extensive libraries, such as NumPy, Pandas, NetworkX and SciPy, to handle the distance matrix, perform computations and evaluate results systematically. Python's flexibility and robust ecosystem ensured efficient and execution and accurate comparisons of the algorithms, providing reliable insights into their effectiveness for solving the Traveling Salesman Problem (TSP).

Travelling Salesman Problem (TSP)

The Travelling Salesman Problem (TSP) aims to find the shortest route that starts and ends at the same hub while visiting all other hubs exactly once [5]. The objective is to minimize the total travel distance or time, as expressed by equation:

$$z = \sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{d}_{ij}\,\tilde{x}_{ij} \qquad (1)$$

The constraints ensure that each hub is visited exactly once, with one incoming and one outgoing route for each hub:

$$\sum_{j=1}^{n}\tilde{x}_{ij} = 1, \qquad i = 1, 2, 3, \dots, n \qquad (2)$$

$$\sum_{i=1}^{n}\tilde{x}_{ij} = 1, \qquad j = 1, 2, 3, \dots, n \qquad (3)$$

where

$\tilde{d}_{ij}$	=	distance or time between hub *i* and *j*,
$\tilde{x}_{ij}$	=	binary decision variable indicating whether travel occurs between hub *i* and *j*

This study employs dynamic programming, genetic algorithms, and simulated annealing to solve the TSP. The problem is asymmetric, meaning the travel distances or times between hubs may differ based on the direction of travel, accurately reflecting real-world delivery scenarios. This approach ensures comprehensive and efficient optimization of delivery routes.

Dynamic Programming (DP)

Dynamic Programming (DP) is an effective method for solving the TSP by storing and reusing intermediate results. Chauhan et al. (2012) introduced a layered network model for TSP, denoted G* = (V*, A*), which consists of *n*+1 layers corresponding to tour positions, with the home city acting as both the starting and ending point [7]. This structure links feasible tours to the shortest paths in the network.

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The DP approach involves several key steps: selecting an initial city *IS*, generating a power set χ of remaining cities and iterating through combinations. The cost function is initialized with $g(k,\phi) = C_{k1}$ and updated using:

$$g(i,E) = \min_{j\epsilon E}\left(C_{ij} + g(j, E - \{j\})\right) \tag{4}$$

The minimum cost to return to the starting city is computed as:

$$g(1, S - \{1\}) = \min_{j\epsilon S-\{1\}}\left(C_{ij} + g(j, S - \{1\} - \{j\})\right) \tag{5}$$

where

C_{ij}	=	Cost of traveling from city i to city j
E	=	A subset of cities that remain to be visited
S	=	The set of all cities excluding the starting city

The time complexity of this DP solution is approximately $O(n^2 \cdot 2^n)$, due to the exponential number of subsets. Overall, this technique efficiently finds optimal solutions for TSP while minimizing redundant calculations through memorization, making it suitable for problems classified as nondeterministic polynomial time.

Genetic Algorithm (GA)

The genetic algorithm (GA), inspired by the principle of natural selection, is a meta-heuristic technique that operates using three key processes: selection, crossover and mutation. These processes are guided by parameters that significantly influence the algorithm's performance. The selection operator identifies the fittest individuals based on a fitness function, ensuring that high-quality solutions propagate to the next generation while the crossover and mutation operators facilitate reproduction and introduce diversity, exploring the solution space effectively. In the context of transportation logistics, where the goal is to minimize distance and cost in distribution network, the performance of the GA can be enhanced by adjusting key parameters: population size, crossover probability and mutation probability [8]. Figure (a) illustrates the flowchart of the Genetic Algorithm (GA). The process begins with an initial population and utilizes selection, crossover and mutation to address problems.

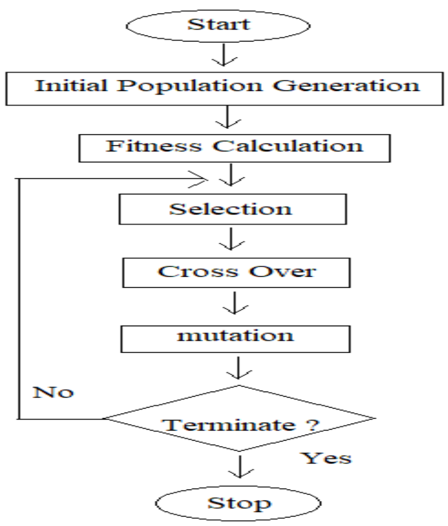

Fig. 1 Flowchart of Genetic Algorithm

The population size determines the number of individuals (chromosomes) in each generation, impacting both diversity and computational efficiency. Various population sizes were tested to identify the optimal size for route optimization. Crossover probability governs how often the crossover operator is applied, combining genetic material from two parent chromosomes to create offspring. Different crossover probabilities were experimented with to assess their impact on performance. A one-point crossover was used, where sub-tours from two parent routes are swapped to generate new solutions. A higher crossover probability promotes the transmission of advantageous traits but must be balanced to avoid premature convergence.

The mutation probability introduces random changes to a chromosome, maintaining genetic diversity and preventing early convergence. Mutation probabilities were tested to explore their effect on the algorithm's ability to explore the solution space. In the Traveling Salesman Problem, mutations could involve rearranging cities along a path, helping the GA escape local optima and explore a broader solution space. By adjusting these parameters, the GA can be fine-tuned to effectively solve complex root optimization problems and sharing a balance between aspirations and exploitation of the solutions space [9].

1	2	5	4	3	6	9	8	7	10	1

1	8	3	4	5	2	7	6	9	10	1

(a) (b)

Fig. 2 Parent chromosomes (a) 1st parent chromosomes, (b) 2nd parent chromosomes

For instance, the crossover operation in the genetic algorithm (GA) for the TSP involves a single-point crossover at a designated city, such as city 5. Parent chromosomes are split at this point, with cities from parent 1 copied into cities from parent 2 copied into child 2 up to the crossover point. For the remaining cities, the nearest-neighbor approach is used to select the next city based on the shortest distance. This ensures that the offspring inherits optimal traits while improving the solution. This process is applied to both children, generating complete routes. This modified crossover enhances the algorithm's ability to explore and exploit the solution space, improving performance in TSP challenges.

Simulated Annealing (SA)

Simulated Annealing (SA) is a powerful method used to solve complex optimization problems, like TSP. It is inspired by the annealing process in metallurgy, which reduces defects through controlled cooling [10]. The algorithm starts with an initial solution and iteratively explores nearby solutions. If a new solution is better, it replaces the current one; if worse, it may still be accepted based on a probability determined by the temperature parameter, calculated using:

$$P(\alpha) = C \cdot \exp\left(-\frac{E_{conf}}{T}\right) \tag{6}$$

where

T = temperature

C = normalization constant

E_{conf} = configuration energy

In Simulated Annealing, the key parameters—temperature (T), normalization constant (C), and configuration energy (Econf) play a crucial role in balancing exploration and exploitation. The temperature controls the acceptance of worse solutions, allowing broader exploration at higher values and promoting convergence at lower values. The normalization constant scales, the temperature and energy values, influencing the probability of accepting worse solutions. Configuration energy represents the objective function value and determines the acceptance probability based on the energy difference between solutions. The cooling schedule, typically exponential, gradually reduces the temperature, ensuring that the algorithm starts with extensive exploration and eventually focuses on refining the solution. The rationale behind these parameters is essential for optimizing SA's performance and ensuring reproducibility, as their values and schedules directly impact the algorithm's ability to escape local optima and find a global optimum.

As the algorithm progresses, the temperature decreases, reducing the likelihood of accepting worse solutions [11]. This process allows for a broader search for global optima while gradually refining the solution space, effectively balancing exploration and exploitation in complex optimization landscapes.

Furthermore, Simulated Annealing permits uphill moves to escape local optima by relying on randomization. It evaluated neighbors in random order, moving to the first one that improves the solution or satisfied a random acceptance test based on a temperature parameter. This parameter decreases over time, simulating the annealing process where higher temperatures allow larger uphill movements and lower temperature reduce their likelihood. At zero temperature, SA becomes a randomized iterative improvement algorithm that rejects all uphill moves.

SA has been widely applied to problems like the Traveling Salesman Problem (TSP), demonstrating effectiveness in large-scale combinatorial optimization. Johnson et al. (1995) highlighted the importance of temperature schedules and neighborhood definitions [12].

Assumptions and Comparative Analysis of Algorithms

The study operates under the assumption that delivery route data is measured in kilometers for distance and minutes for time with distance record in decimals. The research employed the DP, GA and SA to develop models for optimizing the delivery routes between hubs in Johor, utilizing Python for precise and efficient model development and solution analysis. The model allows users to input data, which is then processed to generate optimal solutions. DP served as the benchmark for performance evaluations, with GA and SA compare against it to assess which method yields results closer to DP. The evaluations focused on delivery distance and time, aiming to highlight the strengths and weaknesses of GA and SA as alternatives to DP in route optimization.

RESULTS AND DISCUSSION

Preliminary Analysis

In this study, three optimization algorithms DP, GA and SA were employed to establish optimal delivery routes between J&T hubs in Johor. The primary objective was to assess the effectiveness of these algorithms in improving delivery route efficiency by minimizing the total distance and time travelled. Dynamic Programming (DP) provided a solution with a total distance of 696.40 km. The route sequence generated was Kukup → Nusa Sentral → Nusa Bestari → Larkin → Ulu Tiram → Pasir Gudang → Desaru → Tenggaroh → Taman Emas → Penggaram → Parit Jawa → Tangkak → Pagoh → Bukit Batu → Kelapa Sawit → Kulai → Kangkar Pulai → Pulai Mutiara → Kukup. The result is shown in Table 2.

Table 2 Delivery Route Sequence based on Distance Optimized by DP

Node	Hub Name	Sequence	Route	Distance (km)
1	Kukup	1	1→ 7	33.6
7	Nusa Sentral	2	7→ 2	8.1
2	Nusa Bestari	3	2→ 4	12.5
4	Larkin	4	4→ 9	14.7
9	Ulu Tiram	5	9→ 8	25.7
8	Pasir Gudang	6	8→ 18	45.6

18	Desaru	7	18→ 16	85.9
16	Tenggaroh	8	16→17	73.1
17	Taman Emas	9	17→ 15	89.1
15	Penggaram	10	15→ 12	41.9
12	Parit Jawa	11	12→ 14	37.5
14	Tangkak	12	14→ 13	34.3
13	Pagoh	13	13→ 5	109.0
5	Bukit Batu	14	5→ 11	11.5
11	Kelapa Sawit	15	11→ 10	12.1
10	Kulai	16	10→ 6	14.4
6	Kangkar Pulai	17	6→ 3	8.8
3	Pulai Mutiara	18	3→ 1	38.6
Total Distance travelled (km)				696.40

Table 3 Delivery route sequence based on distance optimized by GA

Node	Hub Name	Sequence	Route	Distance (km)
5	Bukit Batu	1	5→13	108
13	Pagoh	2	13→14	34.7
14	Tangkak	3	14→12	38
12	Parit Jawa	4	12→15	41.3
15	Penggaram	5	15→17	89
17	Taman Emas	6	17→16	73.1
16	Tenggaroh	7	16→18	85.8
18	Desaru	8	18→8	45.7
8	Pasir Gudang	9	8→9	24.8
9	Ulu Tiram	10	9→4	18.5
4	Larkin	11	4→2	11.9
2	Nusa Bestari	12	2→7	7.3
7	Nusa Sentral	13	7→1	35.9
1	Kukup	14	1→3	38.5
3	Pulai Mutiara	15	3→6	7.9

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6	Kangkar Pulai	16	6→10	14.3
10	Kulai	17	10→11	12.2
11	Kelapa Sawit	18	11→5	11.4
Total Distance travelled (km)				698.30

Genetic Algorithm (GA) and Simulated Annealing (SA) also produced viable solutions, with GA yielding a total distance of 698.30 km and SA resulting in 727.10 km. These results illustrated the practical application of these three algorithms in solving complex route optimization problems.

By employing these three methods, this study demonstrates their capability to identify efficient delivery routes, offering valuable insights into optimizing logistics operations. The findings highlight the potential of DP, GA and SA as effective tools for solving real-world route optimization challenges. Table 2, 3 and 4 summarize the outcomes of the algorithms and their application in this context.

Table 4 Delivery route sequence based on distance optimized by SA

Node	Hub Name	Sequence	Route	Distance (km)
13	Pagoh	1	13 → 14	34.7
14	Tangkak	2	14 → 12	38
12	Parit Jawa	3	12 → 15	41.3
15	Penggaram	4	15 → 1	93.3
1	Kukup	5	1 → 7	33.6
7	Nusa Sentral	6	7 → 2	8.1
2	Nusa Bestari	7	2 → 3	17.4
3	Pulai Mutiara	8	3 → 6	7.9
6	Kangkar Pulai	9	6 → 5	32.9
5	Bukit Batu	10	5 → 11	11.5
11	Kelapa Sawit	11	11 → 10	12.1
10	Kulai	12	10 → 4	29.3
4	Larkin	13	4 → 9	14.7
9	Ulu Tiram	14	9 → 8	25.7
8	Pasir Gudang	15	8 → 18	45.6
18	Desaru	16	18 → 16	85.9
16	Tenggaroh	17	16 → 17	73.1
17	Taman Emas	18	17 → 13	122
Total Distance travelled (km)				727.10

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Optimization of Delivery Routes: Minimizing Distance and Time

This analysis highlights the effectiveness of three algorithms in logistic optimization, particularly in determining efficient delivery routes. The study focuses on determining the most efficient algorithm based on two key factors: minimizing travel distance and accounting for variations in time periods (weekdays and weekends). By leveraging a distance matrix, the analysis ensures precise calculations of travel distances between cities, enabling each algorithm to identify optimal routes.

In addition to considering distance, the analysis also evaluates delivery routes over two distinct periods: weekdays and weekends. This temporal distinction is critical for reflecting variations in traffic patterns, delivery schedules and customer demand. By incorporating these two periods, DP identifies optimal routes that account for practical constraints and real-world conditions, ensuring the solutions are not only theoretically efficient but also operationally viable. The results confirmed the DP's ability to adapt to dynamic scenarios, providing tailored recommendations that optimize both the distance and time across different periods.

The results generated by DP identified optimal delivery routes based on both distance and time. For the shortest distance, the optimal route sequence is Kukup → Nusa Sentral → Nusa Bestari → Larkin → Ulu Tiram → Pasir Gudang → Desaru → Tenggaroh → Taman Emas → Penggaram → Parit Jawa → Tangkak → Pagoh → Bukit Batu → Kelapa Sawit → Kulai → Kangkar Pulai → Pulai Mutiara, covering a total distance of 696.40 km, as shown in Table 5.

Table 5 Delivery route sequence based on distance travelled optimized by DP

Node	Hub Name	Sequence	Route	Distance (km)
1	Kukup	1	1→ 7	33.6
7	Nusa Sentral	2	7→ 2	8.1
2	Nusa Bestari	3	2→ 4	12.5
4	Larkin	4	4→ 9	14.7
9	Ulu Tiram	5	9→ 8	25.7
8	Pasir Gudang	6	8→ 18	45.6
18	Desaru	7	18→ 16	85.9
16	Tenggaroh	8	16→17	73.1
17	Taman Emas	9	17→ 15	89.1
15	Penggaram	10	15→ 12	41.9
12	Parit Jawa	11	12→ 14	37.5
14	Tangkak	12	14→ 13	34.3
13	Pagoh	13	13→ 5	109.0
5	Bukit Batu	14	5→ 11	11.5
11	Kelapa Sawit	15	11→ 10	12.1
10	Kulai	16	10→ 6	14.4
6	Kangkar Pulai	17	6→ 3	8.8

3	Pulai Mutiara	18	3→ 1	38.6
Total Distance travelled (km)				696.40

Table 6 Delivery route sequence based on time (10 p.m. Weekdays) using DP

Node	Hub Name	Sequence	Route	Distance (km)
1	Kukup	1	1 → 2	39
2	Nusa Bestari	2	2 → 4	16
4	Larkin	3	4 → 9	24
9	Ulu Tiram	4	9 → 8	26
8	Pasir Gudang	5	8 → 18	39
18	Desaru	6	18 → 16	68
16	Tenggaroh	7	16 → 17	62
17	Taman Emas	8	17 → 15	89
15	Penggaram	9	15 → 12	43
12	Parit Jawa	10	12 → 14	46
14	Tangkak	11	14 → 13	27
13	Pagoh	12	13 → 5	67
5	Bukit Batu	13	5 → 11	14
11	Kelapa Sawit	14	11 → 10	17
10	Kulai	15	10 → 6	17
6	Kangkar Pulai	16	6 → 3	16
3	Pulai Mutiara	17	3 → 7	20
7	Nusa Sentral	18	7 → 1	37
Min time Delivery (min)				667

For time optimization during weekdays, the best departure time is 10 p.m., with a total travel time of 667 minutes. The optimal route sequence is Kukup → Nusa Bestari → Larkin → Ulu Tiram → Pasir Gudang → Desaru → Tenggaroh → Taman Emas → Penggaram → Parit Jawa → Tangkak → Pagoh → Bukit Batu → Kelapa Sawit → Kulai → Kangkar Pulai → Pulai Mutiara → Nusa Sentral → Kukup. On weekends, the optimal delivery route also departs at 10 p.m., achieving a total travel time of 641 minutes. The sequence is Nusa Bestari → Nusa Sentral → Kukup → Pulai Mutiara → Kangkar Pulai → Kulai → Kelapa Sawit → Bukit Batu → Pagoh → Tangkak → Parit Jawa → Penggaram → Taman Emas → Tenggaroh → Desaru → Pasir Gudang → Ulu Tiram → Larkin → Nusa Bestari. These results demonstrated the effectiveness of DP in determining efficient delivery routes tailored to both distance and time constraints. The results are shown in Table 6 and Table 7, respectively.

Table 7 Delivery route sequence based on time (10 p.m. Weekends) using DP

Node	Hub Name	Sequence	Route	Distance (km)
2	Nusa Bestari	1	2 → 7	12
7	Nusa Sentral	2	7 → 1	35
1	Kukup	3	1 → 3	46
3	Pulai Mutiara	4	3 → 6	13
6	Kangkar Pulai	5	6 → 10	19
10	Kulai	6	10 → 11	17
11	Kelapa Sawit	7	11 → 5	13
5	Bukit Batu	8	5 → 13	63
13	Pagoh	9	13 → 14	28
14	Tangkak	10	14 → 12	42
12	Parit Jawa	11	12 → 15	41
15	Penggaram	12	15 → 17	87
17	Taman Emas	13	17 → 16	61
16	Tenggaroh	14	16 → 18	65
18	Desaru	15	18 → 8	40
8	Pasir Gudang	16	8 → 9	23
9	Ulu Tiram	17	9 → 4	21
4	Larkin	18	4 → 2	15
Min time Delivery (min)				641

In conclusion, Dynamic Programming (DP) proved to be a superior method for solving Travelling Salesman Problem (TSP) compared to Genetic Algorithms (GA) and Simulated Annealing (SA). DP consistently delivers optimal solutions by systematically exploring all possible routes and utilizing a distance matrix for precise calculations, ensuring accurate route selections. While GA and SA offer heuristic approaches that can be effective in certain scenarios that often rely on probabilistic methods and parameter tuning, which may lead to inconsistent results. Overall, DP's reliability and guaranteed optimality make it the preferred choice for logistic optimization tasks, particularly when accuracy and efficiency are crucial.

Comparison of Algorithm Performance

The results shown in Table 8 and Fig.3 highlight the comparative performance of GA and SA in optimizing delivery routes. GA achieved a shorter total distance of 698.30 km compared to SA’s 727.10 km, indicating GA’s higher efficiency in route optimization. This difference indicates GA’s ability to generate solutions that are closer to the optimal route, reducing the overall travel distance required.

On weekdays, GA consistently outperformed SA in travel times across all time slots. For instance, at 6 p.m., a peak traffic period, GA recorder a travel time of 723 minutes, whereas SA took significantly longer at 764

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minutes. Similarly, at 10 p.m., GA achieved a travel time of 679 minutes, compared to SA's 726 minutes, showing its efficiency even during off-peak hours. The smallest difference was observed at 8 a.m., where GA recorded 721 minutes and SA recorded 730 minutes, still favouring GA.

On weekends, GA maintained its superior performance in most time slots. At 10 p.m., GA recorded a travel time of 646 minutes, compared to SA's 654 minutes, highlighting its ability to optimize routes effectively during non-working days. However, an exception occurred at 6 p.m., where SA slightly outperformed GA, recording a travel time of 720 minutes, compared to GA's 742 minutes. Despite this anomaly, GA provided better results overall.

These findings underline the advantages of GA's population-based search approach, which evaluates multiple solutions simultaneously, enabling it to explore a broader solution space and avoid local optima. In contrast, SA's reliance on a cooling schedule for optimization makes it more sensitive to parameter tuning, which could result in less consistent performance. Overall, GA demonstrated superior performance in minimizing both distance and travel time, making it a more effective method for optimizing delivery route compared to SA.

Table 8 Algorithm Performance Comparison: GA vs. SA

		GA	SA
Distance (km)		698.30	727.10
Weekdays (minutes)	8 a.m.	721	730
	1 p.m.	710	744
	6 p.m.	723	764
	10 p.m.	679	726
Weekends (minutes)	8 a.m.	693	697
	1 p.m.	706	727
	6 p.m.	**742**	**720**
	10 p.m.	646	654

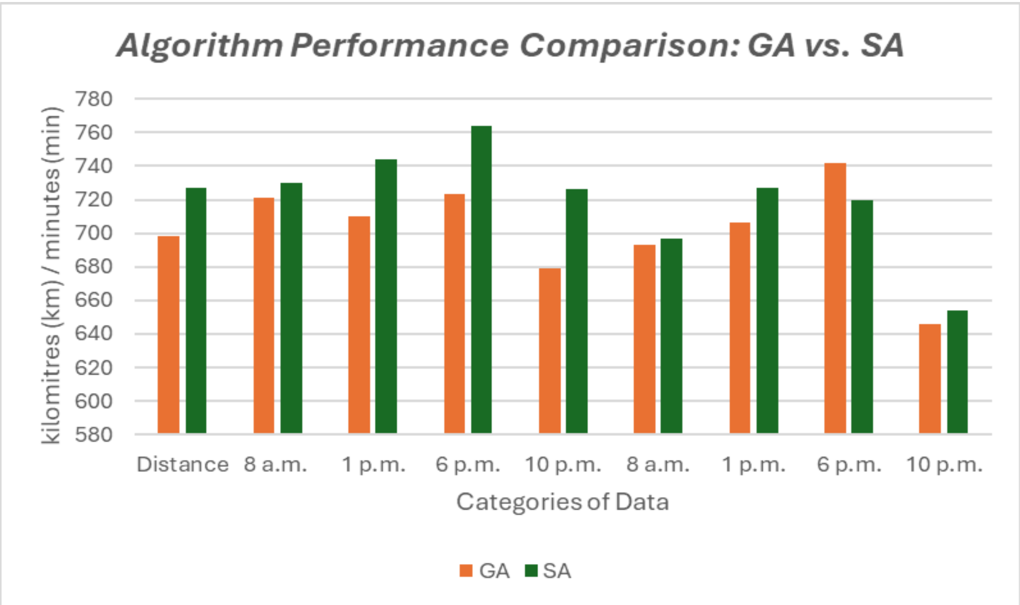

Fig. 3 Algorithm Performance Comparison: GA vs. SA

CONCLUSION

All objectives of this study were successfully achieved. The first objective, to employ Dynamic Programming (DP), Genetic Algorithm (GA) and Simulated Annealing (SA) to establish optimal delivery routes between J&T hubs in Johor, was accomplished using data from 18 hubs and nine datasets analyzed with Python. The second objective, to determine the optimal delivery route considering distance and time, demonstrated DP as the most effective method, consistently providing optimal solutions, while GA ranked second with near-optimal results and SA showed less consistency due to sensitivity to parameter settings. The third objective, to compare GA and SA against DP as a benchmark, revealed that GA outperformed SA in 8 out of 9 cases, delivering results closer to the optimal solutions due to its robust evolutionary processes.

These findings are highly relevant to the e-commerce industry, especially for optimizing last-mile delivery, which is a critical factor in meeting customer expectations and maintaining competitive advantage. By offering near-optimal solutions in complex, resource-constrained environments, GA provides a cost-effective alternative to DP for logistic companies and e-commerce platforms like Shopee and Lazada. Implementing these optimized routes can significantly reduce operational costs, minimize fuel consumption, and improve delivery times, directly enhancing customer satisfaction. For example, businesses operating in densely populated urban areas or regions with high delivery demands can leverage GA to streamline their logistic network. Further studies could expand on these findings by using a larger data set and incorporating dynamic factors such as real-time traffic and weather conditions, making the models more adaptable to real scenarios. Exploring hybrid approaches that combine GA and SA could unlock even greater efficiencies, while applying these models globally would validate their versatility across diverse logistic contexts. Additionally, automating parameter tuning and considering environmental factors like fuel consumption could lead to more sustainable and efficient logistic solutions.

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Conflict of Interest

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:** Kan Ho Li, Suliadi Firdaus Bin Sufahani; **data collection:** Kan Ho Li; **analysis and interpretation of results:** Kan Ho Li, Suliadi Firdaus Bin Sufahani; **draft manuscript preparation:** Kan Ho Li, Suliadi Firdaus Bin Sufahani. All authors reviewed the results and approved the final version of the manuscript.

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