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BALANCING EXPLORATION AND EXPLOITATION IN ANT COLONY SYSTEM FOR WASTE COLLECTION VEHICLE ROUTING PROBLEM WITH TIME WINDOWS

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Abstract:

The Vehicle Routing Problem is a combinatorial optimization problem in logistics aiming to determine optimal routes for a fleet of vehicles servicing a set of customers. The vital challenge in optimizing route efficiency includes reducing total distance, satisfying demand, and vehicle capacity constraints. The Vehicle Routing Problem Time Window introduces time window constraints that reflect real-world scenarios, requiring each customer to be serviced within a specified time interval, thus significantly increasing problem complexity. As the global waste generation is expected to continue to grow worldwide over the coming decades, the demand for the Waste Collection Vehicle Routing Problem with time window is essential. Ant Colony System (ACS) produces high-quality solutions, especially for complex scenarios. However, it leads to the issues of premature convergence and stagnation. This research explored insights using the waste collection benchmark dataset. To further enhance the result, the parameter settings of the parameter values were tuned during testing. The aim is to improve the solution quality by utilizing the exploration and exploitation capabilities of ACS. Experimental results demonstrate performance improvement in reducing the travel distance. Future research should explore the use of hybrid algorithms in actual platforms, considering sustainable logistics, and contribute to a scalable solution for logistics.

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Keywords:

Vehicle Routing Problem (VRP), Waste Collection Vehicle Routing Problem (WCVRP), Ant Colony System (ACS), Exploration, Exploitation

Introduction

Global waste generation is expected to continue increasing worldwide over the coming decades. In 2016, the total waste generation in East Asia and the Pacific amounted to 468 million metric tons. Projections show that by 2050, waste generation in this region will increase to 714 million metric tons due to the increase in population (Rahmanifar et al., 2023). Municipal solid waste (MSW) refers to the waste discarded daily, including food, packaging, and paper. Special waste comprises industrial, medical, electronic, hazardous, and agricultural waste. Thus, with the increase in this waste, effective and competent waste management systems are significant in addressing the problem (Santoso et al., 2024; Rahmanifar et al., 2024).

The Vehicle Routing Problem (VRP) is a classic mathematical optimization problem in logistics and transportation using various formulations and extensions. It finds the optimal routes for a fleet of vehicles to deliver goods to customers while minimizing a specific cost function. The key elements in variations of the VRP are a depot or a central location for the vehicles to start their routes, end their routes, and landfills to dispose of waste (Hu et al., 2024). Customers are a set of collected locations that need to be serviced, and each customer has a specific location or Global Positioning System (GPS) coordinate. A fleet of vehicles refers to a defined number of vehicles available to service customers. A distance or cost matrix provides the travel distances or costs between all pairs of locations (depot and customers). In addition, each vehicle has a capacity limit and needs to return to the depot after disposing of the waste (Markov et al., 2020). Next to be considered are the customer demands on a route, and the driver's working hours must not exceed this limit. The VRP with Time Windows (VRPTW) is one of the VRP variants that has been extensively researched (Kerscher & Minner, 2025). It focuses on customers served within specified time windows before the vehicles return to the depot (Leelertkij et al., 2025). It includes the time window restrictions on depots and disposal facilities (Su et al., 2024). VRPTW is considered an NP-hard problem for large instances, due to the time allocation restriction and the sequence of visits to all customers, landfills, and returning to the depot (Ahmed et al., 2023).

Waste Collection Vehicle Routing Problem (WCVRP) and its variants have been broadly studied. It is a combinatorial optimization problem that efficiently collects waste or distributes products from a central depot to a set of geographically dispersed locations. The goal is to determine the optimal set of routes for a fleet of vehicles to service all the customers while minimizing certain costs or objectives (Delgado-Antequera et al., 2020). In current analysis, researchers have a high interest in VRP, VRPTW, and particularly WCVRP, as the increase in waste generation needs attention and solutions for improving the waste collection system (Jolfaei et al., 2023).

The Ant Colony System (ACS) is a metaheuristic optimization technique inspired by the foraging behavior of ants to solve complex problems. It is one of the popular variants of Ant Colony Optimization (ACO), introduced in 1997 (Dorigo & Gambardella, 1997). ACS extends the basic principles of ACO by incorporating local pheromone updates and an enhanced global

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updating mechanism. It is capable of overcoming stagnation and premature convergence problems faced by ACO (Teng et al., 2024a). Stagnation occurs when ants get stuck too early on a poor solution, while convergence steadily provides the same solution over time, and prevents the algorithm from exploring better solutions. ACS has proven its efficiency in solving combinatorial optimization problems by simulating the behavior of ants in finding optimal paths (Blum, 2024). Respectively, ACS is widely used in VRPTW and its variants studies due to the effective solutions (Teng et al., 2024a; Zhang et al., 2019).

ACS allows ants to construct solutions using both forward and backward phases. It incorporates pheromone updates for all ants' paths and promotes the exploration of diverse solutions. Parameters in metaheuristics can be tuned as they affect the quality of the results. It allows for more flexible and robust solutions, contributing to the efficiency and effectiveness of the search (Tadaros & Kyriakakis, 2024; Wang et al., 2019). However, it requires precise initialization. The optimal values for the parameters depend mainly on the problem and instance. Parameters for ACS are set based on preliminary experiments and literature studies. Therefore, two types of parameter tuning: offline parameter initialization and online tuning. In offline parameter initialization, the values of different parameters are set before executing the algorithm. On the other hand, online parameter tuning allows the parameters to be controlled and updated dynamically during the algorithm execution (El-Ghazali Talbi, 2009).

This paper examines the ACS algorithm for optimizing routes in the VRPTW in waste collection and evaluates the impact of parameter settings on its performance. It analyzes the trade-offs between exploration and exploitation in the ACS, thus improving the ACS's ability. These techniques are to improve routing efficiency, specifically address the constraints of time windows in vehicle routing. Therefore, the aim is to improve the solution quality by utilizing the exploration and exploitation capabilities of ACS.

The following section presents the related literature, followed by an explanation of the methodology and algorithms used. Subsequently, the study describes the experimental results along with the algorithm’s parameter settings. Finally, it concludes with a summary of findings and potential directions for future research.

Literature Review

This section provides an in-depth discussion of VRP, VRPTW, WCVRP with time window, ACO, and ACS algorithms, together with practical approaches using parameter tuning.

Vehicle Routing Problem

VRP has practical applications in transportation, logistics, and supply chain management industries. Solving this mathematical model using optimization algorithms yields the optimal or near-optimal routes for the vehicle fleet. The VRP objective function is to minimize the cost, including total travelling distance, time, and number of vehicles. The choice of the specific VRP variant and solution method depends on the characteristics of the problem, such as the number of customers, vehicle constraints, and the desired level of solution optimality (Dubey & Tanksale, 2023). The specific details of the formulation can be adjusted based on the variant of the VRP and additional constraints, specifically to the problem.

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Vehicle Routing Problem Time Window

VRPTW is an extension of VRP and is a well-known problem in logistics, which optimizes the delivery routes for a fleet of vehicles with specific time windows. A study on the global supply chain has successfully minimized the total supply chain cost of transportation, storage, and operational expenses, while also reducing carbon emissions. The disruptions, such as delays, equipment breakdowns, or transport interruptions, were also taken as real-life constraints (Kuo et al., 2023). In case studies of healthcare or medical need, patients or customers have time-bound and vehicles need to arrive before the specified time window. VRPTW is more complicated than VRP and is considered a hard time window problem (Saksuriya & Likasiri, 2022). VRPTW for parcels is a service for delivery companies to deposit multiple parcels at customers' designated lockers, thereby reducing the need for direct delivery to individual customers. The constraints include the customer demand for delivery, the capacity of the parcel locker, the time windows of each customer, and the vehicle's capacity (V. F. Yu et al., 2022). Apparently, logistics systems for business become more complex, and VRPTW needs to construct efficient routes.

Waste Collection Vehicle Routing Problem with Time Window

VRPTW in the waste collection vehicle routing problem (WCVRP) with time window involves municipal or private waste collection companies that must service a set of collection points, such as household, commercial, industrial, and recycling. WCVRP with a time window has a capacity limit for each vehicle; the sum of the customer demands on a route must not exceed this limit. Each vehicle has a time limit for serving customers and returning to the depot (Liang et al., 2022). Yuliza et al., (2023) discussed the case study of waste collection with time window constraints in Palembang City that includes a rest break between the morning and evening sessions. The Branch and Bound approach used is one of the exact methods and has effectively produced optimal paths, minimizing both distance and travel time. In another investigation on recyclable white glass collections in a region of Geneva, Switzerland, the Adaptive Large Neighbourhood Search (ALNS) algorithm provides significant results (Markov et al., 2020). Next, the Ant Colony Optimization – Sequential Variable Neighbourhood Search Change Step (ACO-SVNSCS) algorithm was used in a study on four waste collection Capacity Vehicle Routing Problem (CVRP) benchmark datasets and improved over the traditional ACO algorithm by having 66.7%, 81.81%, 62.5%, and 77.77% in terms of the best solution. It has succeeded in solving small, medium, and large-scale problems (Sahib et al., 2025).

Ant Colony Optimization

Various algorithms were used to achieve good results, and the ACO metaheuristic algorithm was widely used in VRP. Its flexibility in parameter tuning is an advantage in balancing exploration and exploitation. ACO adapted well to VRP problems and yielded competitive solutions. In the ACO family, parameter tuning settings have the potential to improve results. The success of the ACO algorithm depends on tuning parameters such as α, β, and ρ in adjusting the pheromone evaporation rate and the exploration-exploitation balance (Widayanti et al., 2024; Liu et al., 2024). ACO is a nature-inspired technique that uses the searching behaviour of an ant colony to solve complex optimization problems. The algorithm mimics how ants communicate by laying down a substance, called pheromones, to mark their trails from their nest to food. The pheromones evaporate over time, making shorter paths more attractive to other ants (Zhang et al., 2019).

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Ant Colony System

ACS is one of the variants of the ACO algorithm and is extensively used in VRPTW and other various domains (Teng et al., 2024b). ACS is better suited than classical ACO in incorporating complex constraints such as time windows due to its more refined searching mechanism. Its capabilities in ensuring a stable and effective search, critical for VRPTW's complexity, are preferred. Empirical results show that ACS outperforms classical ACO variants and other heuristics on VRPTW benchmarks.

In ACS, the parameter α represents the importance of the pheromone trail in the ant's decision-making process. Specifically, α controls the relative importance of the pheromone trail versus the heuristic information, such as distance and cost, when ants make decisions about which path to choose (Liu et al., 2024). Thus, the value of α can be adjusted to adapt to the target problem (El-Ghazali Talbi, 2009). Dorigo and Stützle (2004) mentioned that the α value in the ACS algorithm is best set at a lower value, which is 2.00-5.00. Initially, it focuses more on the exploitation. The smaller value of α of pheromone trails provides a better performance and reduces the possibility of premature convergence (B. Yu & Yang, 2011). If α =0, the selection might be the closest customers. It works like a greedy algorithm and is prone to early stagnation. The β value indicates the pheromone update trail for space exploration. If β = 0, only the pheromone is used without using any heuristic bias.

Table 1: ACS Parameters

Parameter	Role in ACS	Effect on Exploitation	Effect on Exploration	Author(s)
α	Pheromone weight	Higher α means that more ants will follow strong trails	Lower α weakens new path discovery	Dorigo (1997)
β	Heuristic Weight	High β reduces reliance on pheromone	Higher β means ants choose edges with a good heuristic (e.g., short distance)	Montemanni et al. (2005)
m	Number of ants	Fewer ants reinforce the best trails quickly	Higher m means many ants spread pheromone widely	Dorigo & Stützle (2004)
ρ	Evaporatio n rate	Lower ρ means persistence in trails and is exploitation	Higher ρ means trails decay faster and is exploration	Dorigo & Blum (2005)
q	Probability threshold	Higher q will determine the best edge choice	Lower q means more probabilistic path choice	Gambardella & Dorigo (1996)
τ	Initial pheromone	Lower τ means ants depend on heuristics and increase more on exploitation	Higher τ means ants sample more randomly and is exploration	Dorigo & Blum (2005)

ACS, which is a colony of ants, uses more than one ant to explore and exploit different paths. The number of ants and the number of iterations can be tuned for better results, which are a higher number of ants with fewer iterations versus fewer ants with more iterations. A higher number of ants and a lower number of iterations gives a diversity of exploration, in which a

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higher number of ants can explore the solution space more thoroughly in each iteration, potentially finding better solutions quickly (Stutzle & Dorigo, 2002). It also allows parallel processing, as each ant's path can be computed independently. However, more ants require more computational resources per iteration, which can be demanding in terms of memory and processing power. Beyond a certain point, adding more ants may not significantly improve the solution quality but will increase computational cost. Table 1 shows the ACS parameters' role and effects on the exploitation and exploration in providing solutions.

Based on the literature, this paper offers important insights into the ACS exploration and exploitation. WCVRP with time windows presents a significant challenge in logistics and is a complex optimization problem that must be addressed efficiently. The common required constraints in finding the shortest distance are vehicle capacity, route capacity, trips to dispose of waste when it reaches the maximum capacity, number of customers, and time windows. ACS's efficient algorithm allows parameter settings to achieve more significant results. Therefore, this research used the ACS algorithms and parameter tuning with benchmark datasets to yield better results in the WCVRP with time window problem.

Methodology

This paper follows four phases: analysis, setting up experimental parameters, parameter tuning, and performance evaluation.

Phase 1: Analysis

This phase performs research analysis using articles and journals of previous research focusing on VRP variants, ACO variants, and prepares the required data. WCVRP time window needs to concentrate constraints on customers and landfills with specific time windows in which they can be serviced or disposed of within these time limits. The maximum volume for each vehicle at any given time during the day is reached when the vehicle hits the maximum weight; it then must go to a disposal facility. It consists of the objective function to minimize the total distance of the routes, where vehicles travel and visit each customer only once. Each vehicle leaves the depot in the morning and returns to the depot at the end of the day. The total demand of all customers served by a single vehicle on a route does not exceed its capacity

Based on the analysis, this study selects the ACS algorithm, which is one of the algorithms with good solutions and is widely used in VRPTW. In addition, ACS provides flexibility to fine-tune its parameters in obtaining optimal solutions.

Phase 2: Setup of Experimental Parameters

This section presents a setup that compares different values of parameter settings to identify higher performance based on the researchers' and previous studies. The parameters were selected based on the capability of each of these parameters in improving the solutions. The ACS values are as follows.

Table 2: ACS Parameter Settings from Previous Research

Type	Details	Suggested ACS Parameters value	Author(s)
Greedy ACS	Ants mostly pick the best next edge exploitation	$\alpha = 1$, $\beta = 2$, $\rho = 0.9$, $q = 0.9$	Lin et al. (2025)

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		$\alpha = 1$, $\beta = 1$, $\rho = 0.9$, $q = 0.9$	Markov et al. (2020)
Diversifying early search	The higher β and lower q push more probability moves	$\alpha = 1$, $\beta = 4$, $\rho = 0.9$	Yuliza et al. (2023)

In Table 2, the Greedy ACS type suggests $\alpha = 1$, $\beta = 1\text{-}2$, $\rho = 0.9$, and $q = 0.9$ values, and ants mostly pick the best next edge exploitation rather than exploration. Meanwhile, the diversifying early search type prefers the higher β and lower q, thus pushing more probability moves. The parameter values suggested are $\alpha = 1$, $\beta = 4$, $\rho = 0.9$, $q = 0.3\text{-}0.5$. Adaptive studies show that adjusting the α, β, and ρ values improves robustness. However, the parameter tuning values may differ for different case studies and data sizes. Therefore, the generated tests were performed using different values of α, β, ρ, and q in Table 2. The experiments for each instance were run 10 times, and the shortest distance was selected.

Phase 3: Parameter tuning

This stage initially utilizes four key parameters in the ACS algorithm, which are α, β, ρ, and q, that can affect the outcomes. Higher α values indicate stronger trails and lower values encourage more exploration. β relies on the heuristic information, and higher values indicate choosing the heuristic information, which tends to choose shorter paths and increases exploitation. If β is low, ants rely less on heuristic information and more on pheromone trails, thus promoting exploration of new routes. Pheromone evaporation rate (ρ) removes old information or outdated trails to avoid getting stuck. The q value balances exploration and exploitation, where a higher value implies ants choose the best-known path, and when it is lower, new routes are chosen.

Table 3: Parameter Settings

Alpha (α)	Beta (β)	Rho (ρ)	q
0.5 & 1.0	2 & 3	0.3 & 0.6	0.6 & 0.9

Table 3 shows that α values are best set to 1 or 2, $\beta = 2$ and 3, $\rho = 0.3$ and 0.6, while $q = 0.6$ and 0.9. Parameter tuning capable of identifying the optimal parameter values in ACS to enhance the solutions of WCVRP.

WCVRP was usually tested using benchmark datasets or real-world case studies. The testing in this study is the benchmark dataset that originates from North America, which consists of 10 instances with a minimum size of 102 customers and a maximum size of 2100 customers (Kim et al., 2006; Sahoo et al., 2005).

Table 4: VRPTW Benchmark Dataset

Instance	No. of Customer	Vehicle Capacity (yards)	Capacity per day (yards)	No. of Depots	No. of landfills
102	102	280	400	1	2
277	277	200	2200	1	1
335	335	243	400	1	4
444	444	200	400	1	1
804	804	280	10000	1	19
1051	1051	200	800	1	2
1351	1351	255	800	1	3

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1599	1599	280	800	1	2
1932	1932	462	2000	1	4
2100	2100	462	2000	1	7

Table 4 shows the benchmark data set constraints and details. These instances have different vehicle capacities, maximum daily capacities, several landfills, and a rest break. Each instances have one depot, a maximum of 500 stops allowed per day for each vehicle, a one-hour rest time from 11:00 am to 12:00 pm, and a speed limit of 40 miles per hour.

Therefore, the initial values for ACS parameter settings were set based on previous studies and tested on five instances of the dataset, which are 101, 277, 335, 444, and 804. In the next section, the computation procedure was carried out to compare the performance using ACS and algorithms.

Phase 4: Performance Evaluation

This phase proceeds with performance evaluation by using the optimal values obtained in Phase 3 and using the same dataset. To verify the results, this phase tested all ten instances. In addition, this phase compared results using different numbers of ants and iterations. This research uses the ACS algorithm and provides competitive results. Based on previous results on parameter settings, it reduces the cost of the tour distance. Conversely, if the goal is to find the best possible solution, more iterations with fewer ants might be more effective.

Results and Discussion

This section describes the results of ACS parameter settings and performance evaluation in determining the best value, which is essential to improving the results.

Result of ACS with Parameter Adjustment

This study experimented with parameter tuning to determine the best parameter values for providing the best possible solutions. The adjustment involves running the algorithm with different values of α, β, ρ, and q, in evaluating the performance, and selecting the values that yield the best results for the specific problem instance or dataset.

TABLE 5: ACS Parameters Tuning

ACS Parameter Settings						
α (Alpha)	**1.0**	**0.5***	**0.5***	**0.5***	**0.5***	**% Improvement Compared to the Initial Parameter Settings**
β (Beta)	**2**	**2**	**3***	**3***	**3***	
ρ (Rho)	**0.3**	**0.3**	**0.3**	**0.6***	**0.6***	
q	**0.6**	**0.6**	**0.6**	**0.6**	**0.9**	
m (Ants)	**5**	**5**	**5**	**5**		
Iterations	**10**	**10**	**10**	**10**		
Results: Miles (Number of vehicles)						
102	192.52 (3)	191.61(3)	187.45 (3)	189.37 (3)	187.28	**2.7%**
277	399.29 (3)	398.82 (3)	387.54 (3)	388.78 (3)	384.82 (3)	**3.6%**
335	212.96 (6)	197.26 (6)	180.73 (6)	179.95	174.39 (6)	**18.1%**

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444	75.23 (11)	74.13 (11)	73.80 (11)	72.73 (11)	72.03 (11)	**4.3%**
804	895.26 (5)	779.93 (5)	735.40 (5)	730.56 (5)	710.56 (5)	**20.6%**

**- Final parameter values selected for further testing*

Table 5 presents the results of parameter testing on five instances in the dataset, which are 102, 277, 335, 444, and 804 (Kim et al., 2006). The ACS parameters tested were α, β, ρ, and q. Initially, the settings were set to α = 1.0, β = 2, ρ =0.3, and q = 0.6, which referred to previous studies. Meanwhile, the number of ants and iterations is set to 5 and 10. The testing used different values to observe the relative differences in the results. The best parameter settings were selected and implemented in the ants and iteration tuning testing. The improvement result using α = 0.5, β = 3, ρ =0.6, and q = 0.9 compared to the initial parameter settings is as in Table 5. Instance 102 improved 2.7%, instance 277 improved 3.6%, instance 335 improved 18.1%, instance 444 improved 4.3% and instance 804 improved 20.6%.

Firstly, the α parameter in ACS is tuned using two values of 1 and 0.5. The results show that α = 0.5 produces a better result compared to α = 1.0. Comparing instance 102, the results α = 0.5 produce a lower cost with 191.61 miles and 3 vehicles. Meanwhile, α = 1.0 travels 192.52 miles and uses 3 vehicles. Based on the results, all instances provide a lower cost using α = 0.5; thus, the next test used the same α value to enhance the results.

In the next experiment, the results between β = 2 and β = 3 show that β = 3 produces better results than β = 2. The result shows that a combination of α = 0.5 and β = 3 produces 187.45 miles with 3 vehicles. While β = 2 uses a slightly higher distance, with a difference of 4.1 miles. All instances have the same pattern of results when switching the values of β = 3. It indicates that a higher value of β increases the heuristic desirability or exploration, where ants move toward good edges even with little pheromone.

The experiment continues with comparing the ρ values of 0.3 and 0.6. Interestingly, the experiment shows that 0.3 produces better results for small instances of 102 and 277. However, compared to ρ = 0.6, big instances of 335, 444, and 804 produce better results. It indicates that the lower value persistent trails and promotes exploitation; meanwhile, higher ρ values mean trails decay faster by using the exploration method. Therefore, this test used ρ = 0.6 to proceed to the next testing.

Finally, for the probability approach, value q = 0.9 was used. All instances produce better results, including the small instances; however, the number of vehicles required is the same. The first instance 102 produces 187.28 miles compared to the initial results of 192.52 miles. The second instance shows the lowest with 384.82 miles. Instance 335 uses only 174.39 miles, which is the shortest distance compared to the others. Next instance, 444 shows a slight difference with 72.03 miles, and finally, instance 804 produced a bigger difference with 710.56 miles. Therefore, these results indicate that the probability of using the deterministic best-edge choice is higher and produces better results for all instances.

These parameter values were identified as the optimal values of exploration and exploitation for use in this research. ACS performed better after tuning because exploration was capable of reducing stagnation problems as ants explored new possible areas, and this acceleration

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enhanced convergence. Generally, selecting a balance between the number of ants and iterations, tailored to the specific problem, yields the best results.

TABLE 6: Tuning of ACS Parameters, Number of Ants, and Iterations

INSTANCE	ACS PARAMETERS				Kim (2006) SA + CROSS local search
	5 Ants 20 Iterations		20 Ants 5 Iterations		
	$\alpha = 0.5$	$\alpha = 1.0$	$\alpha = 0.5$	$\alpha = 1.0$	
	$\beta = 3$, $\rho = 0.3$, $q = 0.9$				
102	**172.90 (3)**	189.86 (3)	181.78 (3)	189.89 (3)	205.1 (3)
277	**381.80 (3)**	382.84 (3)	394.29 (3)	400.53 (3)	527.3 (3)
335	**173.2 (6)**	195.98 (6)	192.61 (6)	197.53 (6)	205.0 (6)
444	**71.26 (11)**	73.78 (11)	74.35 (11)	75.15 (10)	87.0 (11)
804	**691.86 (5)**	851.95 (5)	800.22 (6)	816.23 (5)	769.5 (5)
1051	**2519.69 (17)**	2803.64 (17)	2758.07 (17)	2631.58 (17)	2370.4 (18)
1351	**1000.73 (7)**	1044.87 (7)	1086.66 (7)	1096.73 (7)	1039.7 (7)
1599	**1393.83 (14)**	1590.33 (14)	1441.45 (14)	1546.25 (14)	1459.2 (13)
1932	**1546.68 (16)**	1703.51(17)	1615.18 (16)	1738.14 (16)	1395.3 (17)
2100	**2176.61 (17)**	2382.47(18)	2440.52 (18)	2443.65 (18)	1833.8 (16)

*( ) – The number of vehicles used

Table 6 presents the results of ACS parameter tuning with different numbers of ants (m) and iterations using the optimal value retrieved from the previous tests, which is $\alpha = 0.5$ and 1.0, $\beta = 3$, $\rho = 0.3$, and $q = 0.9$, It was tested on all 10 instances to verify the validity of the optimal parameter values, regardless of the instance size.

The results are analysed from two perspectives. The first test compares the $\alpha = 0.5$ and $\alpha = 1.0$. All instances with $\alpha = 0.5$ produce better results than those with $\alpha = 1.0$. The convergence for $\alpha = 1$ shows that the behaviour is like a greedy algorithm, and if $\alpha > 1$, it leads to rapid emergence or stagnation. All ants follow the same path and construct the same tour, which is less optimal. The lower value of α shows a better performance. Therefore, the comparison results show a significant difference between $\alpha = 0.5$ and $\alpha = 1$. All instances using $\alpha = 0.5$ result in a shorter distance. Thus, $\alpha = 0.5$ provides a better solution and is recommended for use in the VRPTW.

Convergence rate and stagnation are higher for $\alpha = 1.0$ compared to $\alpha = 0.5$. Higher α values can lead to faster convergence. Ants follow higher pheromone concentration, thus reinforcing the optimal or suboptimal paths. However, lower α values allow ants to explore various paths longer, which can delay convergence but increase the potential of finding the global optimum rather than setting premature convergence on a local optimum. A lower value of α relies more on heuristic information, such as distance, in decision-making compared to reliance on pheromone trails. More exploration occurs as ants give less priority to well-travelled paths and are more prone to discover new paths.

Secondly, an investigation on ACS performance by varying the number of ants and iterations between 5 ants and 20 iterations against 20 ants and 5 iterations. A lower number of ants and a higher number of iterations provide resource efficiency as fewer ants indicate lower computational requirements per iteration. In the convergence problem, more iterations allow more refinement to the solution. The pheromone trails have more chances to guide the search process toward optimal or near-optimal solutions. However, it has slower exploration, in which fewer ants may result in slower exploration of the solution space, potentially missing better solutions early on. Another downside is that there is a higher risk of convergence to local optima, especially if the number of ants is too low to provide sufficient exploration diversity.

Parameter settings in the ACS algorithm and the number of iterations affect the performance of the algorithm. A higher number of iterations produces good results compared to a lower number of iterations. Also, the result is better with a low number of ants and higher iterations compared to a higher number of ants with a lower number of iterations. Conversely, increasing the number of iterations with fewer ants produces more variants and is more effective in finding the best possible solution.

Viewing from both perspectives of parameter tuning and number of iterations, for a small instance of 102, $\alpha = 0.5$ with five ants and 20 iterations presents the best result of 172.90 miles with 3 vehicles. In addition, medium-sized instance 1051 and the largest instance 2100 show the same pattern, indicating that a lower α value and higher iterations lead to better results. In a word, tuning ACS parameters establishes optimal exploration and exploitation, contributing to good solution quality and convergence speed. ACS effectively refines solutions, resulting in improved outcomes.

Comparing the result with the previous study, this solution has outperformed some of the instances, indicating that the adjustment of ACS exploration and exploitation can improve the algorithm to be competitive.

Conclusion

This study investigates the capability of parameter tuning in balancing exploration and exploitation of the ACS algorithm in solving VRPTW problems. By fine-tuning these parameters, it identifies an optimal ACS parameter setting that improves solution quality in waste-collection routing and remains competitive on standard VRPTW benchmarks.

Common problems in the ACS algorithm are premature convergence and balancing the stagnation of exploration and exploitation. This research aims to improve the solution quality by utilizing the exploration and exploitation capabilities of the ACS algorithm. It demonstrates good performance solutions with suitable parameter tuning of α, β, ρ, and q, as well as refinement of the number of ants and iterations. Using a high α value, ants tend to follow a path with higher pheromone, resulting in stronger exploitation. It converges faster but may risk premature convergence on suboptimal solutions, as it discourages the exploration of new paths. Using a low α value, ants rely more on heuristic information and have more exploration to discover new paths. It indicates that the approach achieves better solution quality and convergence speed. Therefore, a balance of exploration and exploitation of ACS parameters determines the performance of the solutions and improves the route selection.

The experimental results using a benchmark dataset demonstrate that parameter tuning in ACS improves convergence and solutions in solving the WCVRP. By addressing premature convergence and stagnation, the ACS algorithm contributes to more efficient and sustainable waste collection logistics. Future research should focus on hybrid algorithms, adaptive

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parameter tuning, and large-scale real-world applications, with an emphasis on green and sustainable logistics.

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