Green Logistics by a Comparative Study of ACO, GA, and Hybrid ACO-DRL Approaches for Minimizing CO2 Emissions

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Green Logistics by a Comparative Study of ACO, GA, and Hybrid ACO-DRL Approaches for Minimizing CO2 Emissions

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Abstract

The paper focuses on logistics route optimization by Ant Colony Optimization (ACO), Genetic Algorithm (GA) and a Hybrid (ACO-DRL) Deep Reinforcement Learning model to reduce CO2 emissions. The work presented in the paper uses K-means clustering of the dataset containing the UPS Warehouse location and Drop Box location based on geographic coordinates. ACO performed better than GA and ACO-DRL in most of the clusters and proved to be more efficient in minimizing the travel distance and thus CO2 emission. GA was underperforming in dealing with the optimization and produced the highest emission. The hybrid ACO-DRL model perform well in one of the clusters compared to ACO and GA. ACO is identified as the most accurate model to optimize the routes and incorporating it with DRL is seen to offer better results in certain circumstances and thereby reduce the CO2 emission.

1 Introduction

The logistics sector is critical in the global economy as it is involved in the movement of goods over long distances to get to the consumers and markets as desired. However, transportation is also a significant factor of environmental pollution mainly because of the CO2 emissions from transporting vehicles. Also to mention that the logistics industry has the highest CO2 emission, the image below gives the 2022 emission which is 28% of greenhouse gas emissions done by the transportation sector U.S. Environmental Protection Agency (2024).

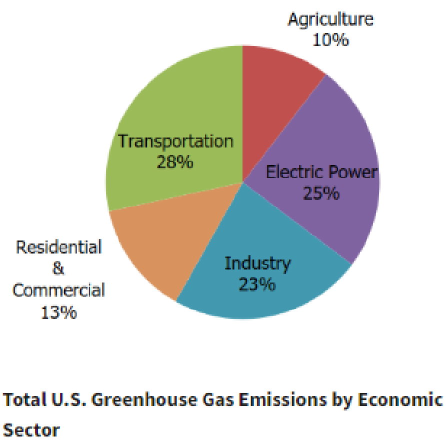

Figure 1: Pie chart of greenhouse gas emission

Source: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

Mariano et al. (2017) had revealed, The relationship between CO2 emissions and logistics performance is not only significant but also complex, The study shows that if there were any improvements in logistics efficiency, the environmental impact of global trade would be minimized which obviously would be an advantage for more sustainable trade practices worldwide. Scholars like Xu and Xu (2022) point out that in countries with higher R and D investments with incentive regulations have strong positive effect on energy efficiency in most regions, mandatory rules have not necessarily lead to consistent CO2 reduction as there may be lapse in enforcement and regional diversity in the policy implementation.

By developing a successful route optimization strategy, the negative effects of the vehicles can be minimized and enhance the business. With advanced algorithms like Ant Colony Optimization (ACO), Genetic Algorithms (GA) and Hybrid Models such as Ant Colony Optimization-Deep Reinforcement (ACO-DRL) using Proximal Policy Optimisation (PPO) have shown potential in providing more efficient solutions. A significant step in this process involves the use of K-means clustering to segment the logistics network allowing an effective application of the optimization algorithms.

ACO inspired by the foraging behavior of ants and GA based on the principles of natural selection and genetics offer promising approaches to solving complex optimization problems. DRL is an advanced ML technique that repeats and refines logistics routes, learn optimal solutions for minimizing travel distance and fuel consumption in complex environments. These algorithms have been applied in various fields demonstrating their potential to find near-optimal solutions efficiently. In the context of logistics these algorithms can be leveraged to optimize routes in a way that reduces C02 emission. This research will seek to address this gap by comparing the performance of these algorithms with a view of identifying how they can improve logistics routes and reduce C02. The CO2 emission is calculated as CO2 Emissions (kg) = Fuel Consumption (liters) $\times$ Emission Factor (kg CO2 per liter) where Fuel Consumption is the total fuel used and Emission Factor is a constant that represents the amount of CO2 produced per liter of fuel burned. Thus, based on the predefined values of the emission factor that is 2.31kg of CO2 per liter of fuel this study aims to offer an evaluation of the realistic usability of these algorithms in the context of logistics U.S. Environmental Protection Agency (2024).

This research paper is guided by the question "How effective is Ant Colony Optimization (ACO) compared to Genetic Algorithms (GA) and Hybrid Models such as ACO-DRL have shown potential to provide more efficient solutions for improving logistics routes to reduce CO2 emissions and fuel consumption and while maintaining logistics efficiency?" The paper's objective is to design a routing model for minimizing the distance and reducing fuel consumption and hence CO2 emissions.

However, it is necessary to mention some limitations of the study, although the work is designed to offer a broad analysis, the research will use assumed fuel consumption and CO2 emissions factor values which may not necessarily represent real-life scenarios. Also, the study is confined to the comparison of ACO, GA and ACO-DRL with the exclusion of other possible optimization methods. This report is organized into several key sections: 1. Related Work in which the previous work is discussed, 2. Research Methodology will give the detailed steps involved 3. Design Specification will give the design of the methods 4. Implementation will discuss the steps to implement the methods 5. Results and Discussion will discuss the outcome and the last section 6. Conclusion and future work section will conclude with what studies can be carried forward.

2 Related Work

The review describes these comprehensive evaluation techniques and explains how they contribute to logistics efforts to reduce their carbon footprints.

2.1 Green Logistics and Sustainability in Transportation

? study how green logistics across different territories work, which can help put into perspective the processes of introducing environmentally friendly measures Setiawan and Koestoer continue the discussion begun by Karaman et al. (2020) focusing on the regional aspect of logistics considerations. According to their findings, ACO depends on the regional factors and logistics networks. However, Karaman et al. (2020), they did not get into the depth of the technological possibilities that could improve these practices, which means identifying yet another issue in the literature. Wang et al. (2020) fills a gap through a discussion on how route optimization techniques can reduce the negative effects on the environment through location-routing decisions. Their work suggests that integrating advanced algorithms like ACO in logistics can significantly enhance environmental sustainability. However, the practical aspects of these implementations remain to be explored, which leads to the next study which focuses on the practical aspects of these implementations, Gevaers et al. (2009) throws light on the practical issues related to the subject by showing as to how improvement in the last mile delivery practices can bring about efficiency improvement as well as sustainability improvement in the logistics chain. The authors suggest the utilization of electric vehicles, drones and best routing algorithms to enhance the last-mile delivery performance and the clients' experience. That is why, the study indicates that sustainable methods should be incorporated into the last-mile delivery which is a major concern of many logistics organizations. The works evaluated in this section highlight the importance of green supply chain management and sustainability reporting to the overall performance of logistics and to the minimization of the environmental effects. Adoption of algorithms and technologies that are innovative is an important way of making the logistics sustainable.

2.2 K Clustering and Route Optimization

Ma et al. (2019) focuses on the efficient arrangement of logistics distribution routes through K-means clustering and mileage-saving algorithms. The authors identified a reducing in total mileage by 25.65 % proving that K-means clustering algorithm is efficient when dealing with numerous and massive data, the study established areas that require enhancement mainly in data cleaning and addressing issues of non-standard distribution. However, further improvement of clustering algorithms can be achieved by including meta- heuristic algorithms, which is discussed in the subsequent research. Şehitoğlu and Aghayeva (2023) enrich the utilization of the K-means clustering in the Capacity Vehicle Routing Problem (CVRP) by comparing the optimal meta-heuristic algorithms that include Ant Colony Optimization (ACO), Tabu Search (TS) and Simulated Annealing (SA), performance was then measured in terms of distance and time. ACO had the shortest time in finding the solution among all the algorithms while TS and SA offered almost similar distance solutions. Following the study of Ma et al. (2019), Şehitoğlu and Aghayeva (2023) proposed the ability to deal with irregular distribution addresses and enhance the overall route plan, the limited scenarios of logistics still pose a problem to the flow of constraints hence, the focus of the next study shall be on the application of the concept. Wang and Zhang (2021) deal with the optimization of B2C e-commerce logistics networks using a constrained clustering algorithm, which makes the optimization more realistic. However, the problem of identifying the initial centers of clusters stays a prominent issue that is discussed in the next work. In Liu (2024), an improved methodology for solving the problem of choosing the initial number of clusters in K-means clustering through the usage of Adaptive-Chaotic Particle Swarm Optimization (AC-PSO) is proposed. After the experiments on benchmark datasets and on the identification of the logistics development levels in 18 cities, it can be concluded that the use of the AC-PSO optimized model provided a higher level of precision in the assessment of the fitness values, and faster convergence rate compared to the K-means, and K-means based on PSO. Liu (2024) study outlines a new approach to the issues raised by other studies, mainly the choice of the initial cluster's centroids. This is because the adaptive and chaotic mapping strategies used in AC-PSO increase the optimization ability, exclude the local optima and increase the clustering accuracy. This enhancement proves the effectiveness of the proposed enhanced K-means model in real-life logistics problems, which translation from theory to practice. By this review, it is understood that clustering algorithms can significantly play an important role in route optimization and reducing CO2 emission by creating clusters and making a better ground of understanding for the algorithms to work upon.

2.3 Route Optimization Algorithms

Zhang et al. (2018) discuss the multi-depot scenarios and try to solve the problem of more complicated locations and route of emergency facilitiesTheir work is focused on the investigation of how new routing algorithms like ACO can minimize CO2 emissions. Ziaei and Jabbarzadeh (2021) describe the challenges and approaches to implementing green multi-modal transportation systems under conditions of risk and uncertainty. Shojaie and Seyedi Bariran (2021) give a detailed comparison of both algorithms ACO and Extended Dijkstra's Algorithm. From the results of this study, it would be clear that while Extended Dijkstra's Algorithm works effectively in a comparatively stable environment, ACO algorithm is more effective in a dynamic environment where the network complexity is more dynamic. Thus, the ACO Algorithm can be considered one of the most effective tools for routing problems that exhibit dynamic behavior, this flexibility is the basic concept of last mile delivery where conditions are dynamic because of traffic, weather and other logistic factors. This evidence is directly related to the research question of the paper as it deals with efficient routing in an attempt to minimize CO2 emissions. The paper proves that ACO could manage the complex routing issues much better which supports the hypothesis as the improved algorithms create the best delivery routes reducing the distance, time and fuel consumption and ultimately lowering the CO2 emissions. The current work builds the groundwork for the succeeding paper Liu et al. (2023), which deals with the improvement of the ACO algorithm through the integration of heuristics and various pheromone evaporation models. The work done by Zhang and Li (2022) concentrates on refining the logistics distribution system. The aim of their study is to enhance route efficiency, trim costs and reduce the carbon footprint associated with logistics operations. For this purpose, they employ Ant Colony Optimization (ACO) algorithm to tackle the Vehicle Routing Problem (VRP). The subsequent research in line with this treats ACO and GA as complementary methods. Wang and Zhao (2021) use ACO and GA in a way that takes advantage of their respective strengths. They model the logistics robot path-planning problem as an optimization problem, then apply a hybrid ACO-GA algorithm to solve it. They found that the hybrid approach achieved a 20% reduction in route length compared to traditional ACO and cut processing time by about 18%. Their application context makes the work a nice fit at the intersection of theoretical strength and practical relevance. Wang and Zhao (2021) tested their framework on a classic routing problem. The results were good but the authors insisted that what they had done was both easier to implement and better in terms of computational performance than what Zhang and Li (2022) had achieved.

2.4 Deep Reinforcement Learning (DRL)

By integrating optimisation techniques with data-driven machine learning approaches, models predict better efficiency, lower costs, and minimized environmental footprint. One of such approaches is explained by Jin et al. (2023) who focus on the problems of DRL the authors propose an optimization method that consists of an Attention Mechanism that helps in filtering unimportant information and a double-DQN method that helps in the efficient storage of data during the training phase. Based on the idea of obtaining the optimum of complicated systems, further research has been conducted by Xu et al. (2024), who used a clustering approach integrated with MARL to improve the effectiveness of taxi dispatching. The division of the operational area into sub-areas by K-means clustering is effective to be applied in route optimization. This approach raises the issue that regional segmentation of a country can be beneficial in the field of logistics. In a similar line of work, Chen et al. (2024) designed a DRL-based scheme for improving the merging strategy of AVs at on-ramps, which includes LK and LC modules. While this study focuses mostly on the problem of merging, the general concepts of DRL based adaptive control and safety supervision introduced herein are particulary useful in logistics, especially when it comes to the issue of multiple vehicle coordination within a fleet. The authors prove that their DRL proposed approach, accompanied by a priority-based safety supervisor improves travel time.

Table 1: Relevant Literature for Logistics Optimization

Title	Authors	Key Focus	Relevance to the Research
Enhanced Vehicle Routing Problem with Capacity Constraints Using K-means Clustering and Ant Colony Optimization	Şehitoğlu and Aghayeva (2023)	Integration of K-means clustering with ACO for solving the Capacity Vehicle Routing Problem (CVRP)	By clustering and applying ACO, GA & ACO-DRL, the logistics efficiency can be improved and CO2 emissions reduced.
Optimization of Logistics Networks Using Hybrid DRL Approaches	Xu et al. (2024)	Hybrid model integrating DRL with clustering techniques to optimize taxi dispatching.	By integrating ACO and DRL, the end result can be more refined.
Ant Colony Optimization for Dynamic Logistics Routing: A Comparative Study	Shojaie and Bariran (2021)	Comparative analysis of ACO and Extended Dijkstra's Algorithm for dynamic logistics routing.	ACO is proven to be the optimal solution and is supported by this paper.

The literature reveals that innovative algorithms like ACO, GA, and hybrid methods substantially improve logistics route optimization and therefore reduce CO2 emissions.

3 Methodology

The purpose of this research is to analyze and compare the results of various route optimization algorithms for reducing CO2 emissions while keeping the logistics performance. By implementing and evaluating ACO, GA and hybrid model (ACO-DRL). This can be achieved by data collection and data pre-processing, clustering of the datapoints and the application of optimization in finding out the best routes. The following sections offer a detailed explanation of each phase.

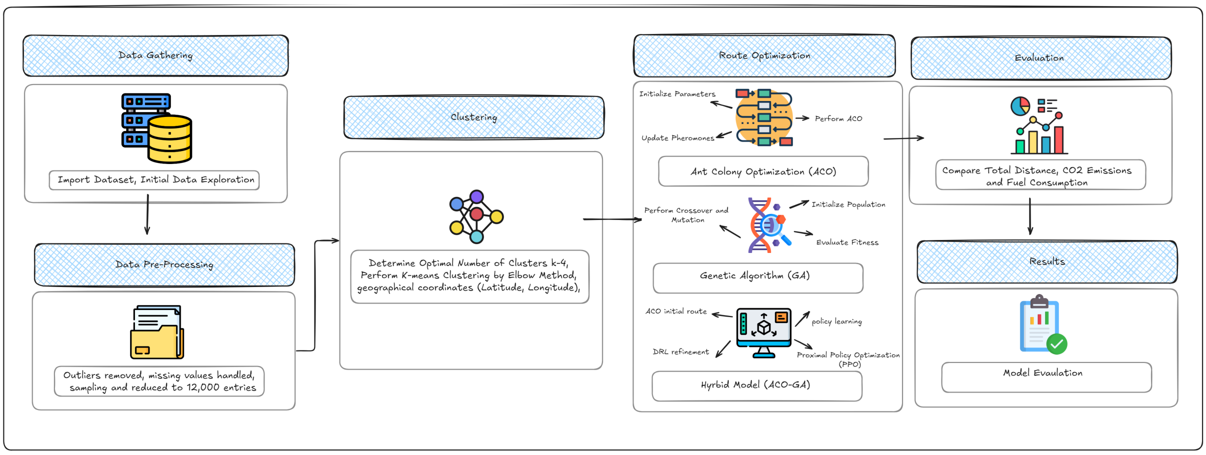

Figure 2: Research Methodology

3.1 Data Collection and Preprocessing

The dataset has information on 49,317 UPS facilities and a drop box in the database with 19 columns: location, address, phone number, and other data. The problem is that outliers which are the islands such as HAWAII ALASKA can greatly distort the picture and therefore were filtered out and only the rows with 'Authorized Shipping Outlet' (the warehouse address) and 'UPS Drop Box'(delivery location address) in the 'NAME' column is kept leaving 42,298 entries. There is only one missing value in the BUSINESSNA column, reducing the dataset to 42,297. For the identification of outliers in LATITUDE and LONGITUDE statistical tool called Interquartile Range (IQR) was used. For the clustering LATITUDE and LONGITUDE were considered, these features gives the geographical co-ordinate. To make the performance of the analysis better, the dataset was sampled by using a proportional stratified sampling method to create a subset of 12,000 rows ensuring correct representation of the distribution of data, keeping the original distribution of the dataset intact. To estimate the environmental impact of the optimized routes, assumptions were made regarding CO2 emission factors and fuel consumption:

1.CO2 Emissions Factors: 2.31 kilograms of CO2 per liter of fuel.

2. Fuel Consumption: 0.12 liter of fuel per kilometer being covered

The CO2 Emission is calculated as: CO2 Emissions = Distance (km) $\times$ Fuel Consumption per km $\times$ CO2 Emissions

3.2 Clustering

K-means clustering is a technique of unsupervised machine learning which is used to segment a given dataset into K different clusters without any overlap. The method which was used to decide the best value of K was the Elbow Method. This method involves the use of Within-Cluster Sum of Squares (WCSS) of different values of K known as 'elbow point'. The best number of clusters to use in the dataset is 4. The results of clustering were visualized by positioning the Longitude and Latitude and each cluster were colored differently.

The geographical distribution reveals the fact that the specified facilities are situated in various regions of the United States of America. Some states and regions of a country have a higher population density of facilities than others. The largest number of facilities are of the "UPS Drop Box" type with 37,112 such facilities. Other facility types are "Authorized Shipping Outlet," "The UPS Store," "UPS Alliance Location," "UPS Customer Center," and a few more. California (CA) is shown to have the highest number of facilities as 5016. Other states with many facilities include Florida (FL), Texas (TX), and New York (NY). Houston, Chicago, Atlanta and Dallas ranked on top on the list of cities with many facilities. Some cities have only one such hub.

Table 2: Cluster Analysis: Numbers of data points per cluster

Cluster	**Number of Facilities**	**Centroid Latitude**	**Centroid Longitude**
0	3,805	40.7128	-74.0060
1	2,993	34.0522	-111.2437
2	2,907	41.8781	-87.6298
3	2,299	29.7604	-95.3698

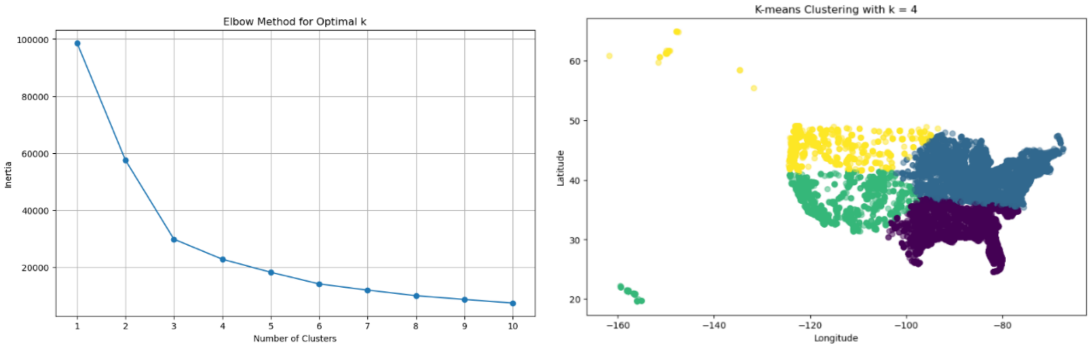

Figure 3: (a) Elbow Method for Optimal k; (b) K-means Clustering with k = 4

These clusters form the foundation on which other algorithms are applied to carry out route optimizations. K=4

To enhance the efficiency of logistics routes and thereby reduce CO2 emission, the implementation and comparison of optimization techniques like Ant Colony Optimization (ACO), Genetic Algorithm (GA) and the hybrid model ACO-DRL has been proposed by the paper. All the methods are based on different strategies for solving the route optimization problem with a focus on reducing distance and thus the CO2 emissions while preserving the logistics conditions. The algorithms are discussed in detail in the next section.

4 Design Specification

4.1 Ant Colony Optimisation (ACO)

For solving the route optimization problem ACO is used in which the ants are made to look for the shortest route and then every ant marks with its pheromones the path it has gone through. The strength of the pheromone is proportional to the quality of the solution, to control the future ant's route to make it shorter and more efficient, this is known as the Pheromone Trails. The solution arrived at by ACO offers a near-optimal solution for the minimum distance of travel. Both the total CO2 emissions and the fuel consumption are computed on the basis of the path which has been optimized. The results affirm that ACO optimally solves the problem of obtaining efficient routes with fewer negative effects on the environment.

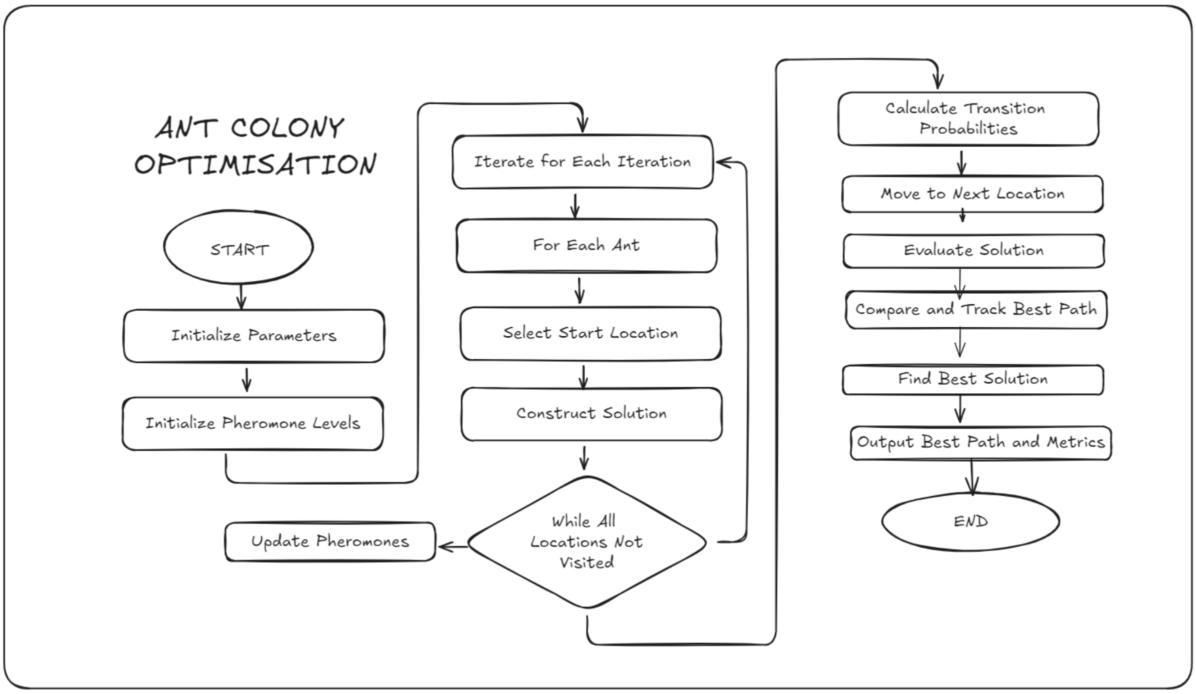

Figure 4: ACO Flowchart

4.2 Genetic Algorithm (GA)

The paper incorporates GA to solve the route optimization problem through the process of natural selection. They are paths that are created with the warehouse as a fixed origination point and a particular drop box as the fixed destination point. A population of routes is evolved by the algorithm through selecting the best individuals and then applying genetic operators of crossover and mutation

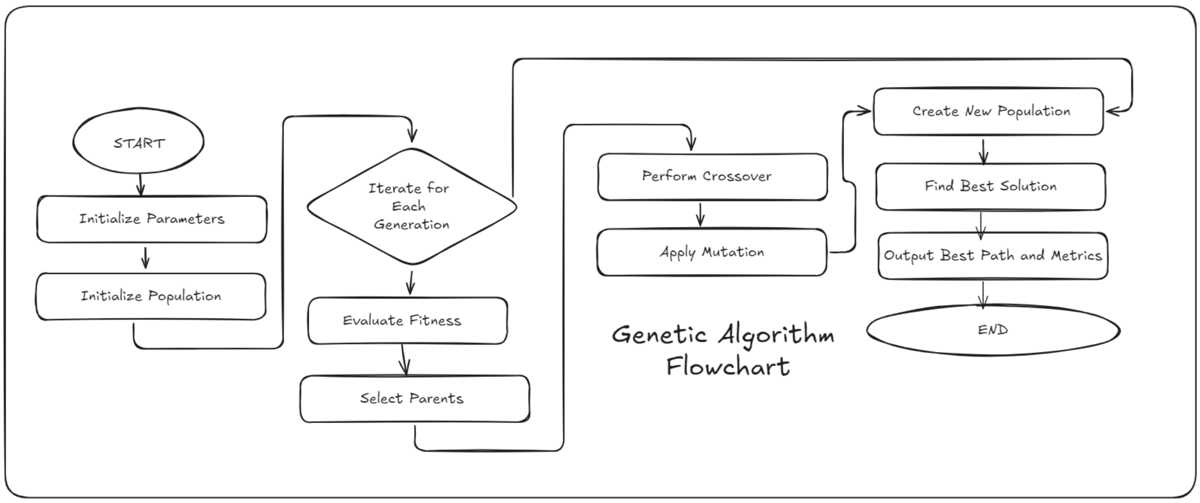

Figure 5: GA Flowchart

4.3 Hybrid Ant Colony Optimisation-Deep Reinforcement Learning (DRL)

The proposed ACO-DRL approach combines advantages of both methods to improve solutions suggested by ACO with the help of learning abilities of DRL. The idea of the proposed approach is to use the advantages of the ACO algorithm for the first route search step and DRL for the subsequent step of applying adaptive learning to improve the identified logistics routes and, thus, achieve more efficient and environmentally friendly solutions.

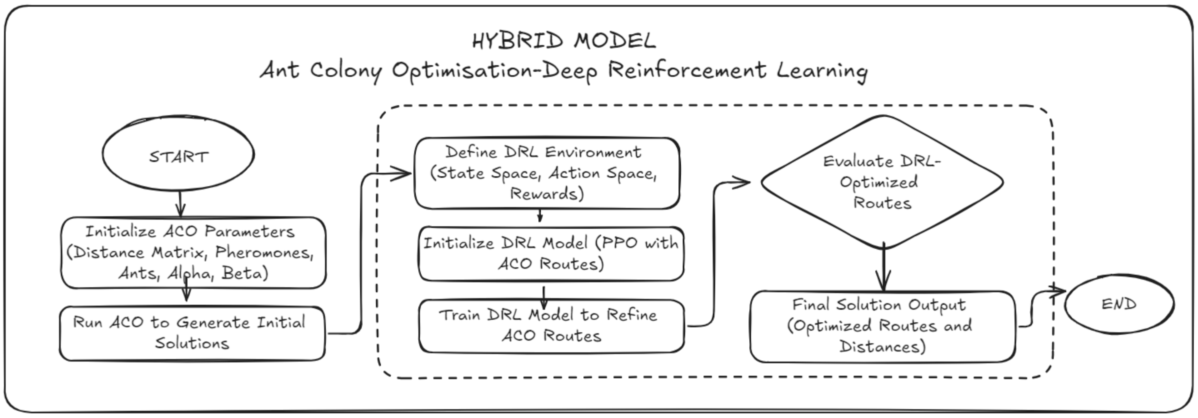

Figure 6: Hybrid ACO-DRL flowchart

Hybrid ACO-DRL Workflow:

1. Initial Route Generation (ACO): The ACO algorithm provides the first solution for the problem, which means that it defines the initial route for each cluster.

2. Environment Setup: This is the first route that is employed to set up the TSP environment in DRL with the specification of start and end points.

3. Model Training (DRL): The PPO algorithm is used to train the DRL model to optimize the initial route by minimizing the total distance through route in reinforcement learning.

4. Refinement and Evaluation: The final route is compared with the ACO route and sees if the refined route is more efficient.

Therefore, by adding an extra layer on ACO and making it a hybrid model, optimised routes can be obtained with the help of DRL.

5 Implementation

A) Table 3 shows the detailed process of implementing the ACO

Table 3: Steps for Implementing the ACO Algorithm

Step	Description	Details
1	Import Necessary Libraries	Import numpy, scipy.spatial.distance_matrix, and other necessary libraries such as pandas for data handling.
2	Define Helper Function	The method ‘safe_normalize(row)‘ is used to normalize a row of probabilities.
3	Iterate Over Clusters	Iterate over each cluster using ‘for cluster_id in sampled_data['Cluster'].unique():‘.
4	Filter Cluster Data	For each cluster, apply the filter to select the warehouse and drop-off points with conditions such as ‘cluster_data[cluster_data['NAME']== 'Authorized Shipping Outlet']‘ and ‘cluster_data[cluster_data['NAME']== 'UPS Drop Box']‘.
5	Combine Warehouse and Drop-Off Points	Concatenate the filtered warehouse and drop-off points DataFrames into a single DataFrame for distance matrix calculation using ‘pd.concat([warehouse.to_frame(), T, drop_boxes])‘.
6	Calculate Distance Matrix	To get the coordinates (LATITUDE, LONGITUDE) and calculate the distance matrix, use ‘distance_matrix(coords, coords)‘. Replace very small values with a positive value of ‘1e-10‘ to avoid division by zero.
7	Set ACO Parameters	Define parameters for the ACO algorithm: ‘n_ants = 10‘, ‘n_best = 3‘, ‘n_iterations = 100‘, ‘decay = 0.95‘, ‘alpha = 1‘, and ‘beta = 2‘.
8	Define ACO Class	Instantiate the ACO class with methods such as ‘__init__‘, ‘run‘, ‘spread_pheromone‘, ‘construct_colony_paths‘, ‘construct_path‘, ‘pick_move‘, and ‘calculate_path_distance‘.
9	Initialize ACO Instance	Create an instance of the ACO class for the current cluster as ‘aco = ACO(dist_matrix, n_ants, n_best, n_iterations, decay, alpha=1, beta=2)‘.
10	Run ACO Algorithm	Call the ‘run()‘ method of the ACO instance to search for the shortest path in the cluster, which creates paths, modifies the amount of pheromones, and stores the shortest path found.
11	Record Results	Capture and print the shortest path and its distance using ‘print(f"Cluster cluster_id: Shortest path: shortest_path[0]")‘ and ‘print(f"Cluster cluster_id: Shortest path distance: shortest_path[1] km")‘.
12	Handle Errors	Incorporate a ‘try‘ and ‘except‘ block when implementing the ACO algorithm for any cluster, so that when an error is encountered, the program does not stop but rather handles the error and continues executing.

B)Table 4 gives the step by step implementation of GA

Table 4: Steps for Implementing the Genetic Algorithm

Step	**Description**	**Details**
1	Import Libraries	Import numpy, random, scipy.spatial.distance_matrix.
2	Define `calculate_total_distance`	Define a function to calculate the total distance for a given route.
3	Define `create_population_fixed_start_end`	Create a population that begins and ends at a set position.
4	Define `evaluate_population`	Determine the fitness of the routes by calculating the inverse of total distance.
5	Define `crossover_fixed_start_end`	Cross over to generate progeny but do not allow the start and end points to change.
6	Define `mutate_fixed_start_end`	Mutate sequences by swapping the locations of two characters, but do not allow either of the characters to be at the start and end points.
7	Define `genetic_algorithm_fixed_start_end`	Raise the operations of the GA to optimize routes across generations.
8	Initialize Population	Create the first routes using the `create_population_fixed_start_end` function.
9	Calculate Distance Matrix	Calculate the distances between locations in a cluster.
10	Evaluate Initial Population	Check the fitness of the first routes using the `evaluate_population` method.
11	Run GA Iterations	Implement the GA over 100 generations to minimize the distance of the routes.
12	Select Parents	Select parents suitable for crossover as it will determine the quality of the offspring.
13	Perform Crossover	Perform crossover to create new offspring routes.
14	Apply Mutation	Mutate offspring to maintain genetic diversity.
15	Update Population	Replace the old population with the new offspring for the next generation.
16	Record Best Route	Find and store the optimal solution from each generation.
17	Print Results	Display the shortest path and the order of the best routes after all generations.

C)Table 5 shows the detailed process of implementing the ACO-DRL hybrid model with the names of steps and values or parameters used in each step.

Table 5: Steps for Implementing the Genetic Algorithm

Step	Description	Details
1	Import Libraries	Import numpy, random, scipy.spatial.distance_matrix.
2	Define `calculate_total_distance`	Define a function to calculate the total distance for a given route.
3	Define `create_population_fixed_start_end`	Create a population that begins and ends at a set position.
4	Define `evaluate_population`	Determine the fitness of the routes by calculating the inverse of total distance.
5	Define `crossover_fixed_start_end`	Cross over to generate progeny but do not allow the start and end points to change.
6	Define `mutate_fixed_start_end`	Mutate sequences by swapping the locations of two characters, but do not allow either of the characters to be at the start and end points.
7	Define `genetic_algorithm_fixed_start_end`	Raise the operations of the GA to optimize routes across generations.
8	Initialize Population	Create the first routes using the `create_population_fixed_start_end` function.
9	Calculate Distance Matrix	Calculate the distances between locations in a cluster.
10	Evaluate Initial Population	Check the fitness of the first routes using the `evaluate_population` method.
11	Run GA Iterations	Implement the GA over 100 generations to minimize the distance of the routes.
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14	Apply Mutation	Mutate offspring to maintain genetic diversity.
15	Update Population	Replace the old population with the new offspring for the next generation.
16	Record Best Route	Find and store the optimal solution from each generation.
17	Print Results	Display the shortest path and the order of the best routes after all generations.

6 Evaluation

This section presents an evaluation of the findings that were derived from the three experiments. The values used to calculate the CO2 is as follows: The co2 emission factor=

6.1 Experiment 1: ACO

Table 6: Results of ACO

Cluster	Number of Points	Distance (km)	Fuel Used (liters)	Estimated CO2 Emissions (kg)
0	3805	442.68	53.12	122.71
1	2299	431.08	51.73	119.49
2	2907	481.29	57.75	133.41
3	2993	564.87	67.78	156.58
Total	**12004**	**1919.91 km**	**230.39 liters**	**532.20 kg**

This table shows the performance of ACO by the evaluation metrices that ACO successfully reduces both distance and CO2 emission.

6.2 Experiment 2: GA

Table 7: Results of GA

Cluster	Number of Points	Distance (km)	Fuel Used (liters)	Estimated CO2 Emissions (kg)
0	3805	16874.58	2024.95	4677.63
1	2299	20421.92	2450.63	5660.96
2	2907	25238.36	3028.60	6996.07
3	2993	17109.29	2053.11	4742.70
Total	**12004**	**79644.15 km**	**9557.30 liters**	**22077.36 kg**

This table refers to the GA performance and the findings indicate that GA is less efficient in this application.

6.3 Experiment 3: ACO-DRL

Table 8: Results of HYBRID MODEL

Cluster	Number of Points	Distance (km)	Fuel Used (liters)	Estimated CO2 Emissions (kg)
0	3805	396.25	47.55	109.84
1	2299	872.58	104.71	241.88
2	2907	819.87	98.38	227.27
3	2993	580.15	69.62	160.82
Total	**12004**	**2668.85 km**	**320.26 liters**	**739.81 kg**

This table depicts the performance of the ACO by the evaluation metrices This table indicates the ACO-DRL performance by the evaluation metrics and it indicates that ACO-DRL can greatly minimize the emission of CO2 in 1 cluster

6.4 Comparative Evaluation of ACO, GA, and ACO-DRL

Cluster 1

Table 9: Results of Cluster 1

Metric	ACO	GA	ACO-DRL	Best Model
CO2 Emissions (kg)	122.71	4677.63	109.84	ACO-DRL
Improvement over GA	97.38%	-	97.65%	ACO-DRL
Improvement over ACO	-	-	10.49%	ACO-DRL

Best Performing Model: ACO-DRL with 97. Achieved 65% better than GA and 10. 49% improvement over ACO.

Cluster 2

Table 10: Results of Cluster 2

Metric	ACO	GA	ACO-DRL	Best Model
CO2 Emissions (kg)	119.49	5660.96	241.88	ACO
Improvement over GA	97.89%	-	95.73%	ACO
Improvement over ACO	-	-	-102.42%	ACO

Best Performing Model: ACO, with a 97.89% improvement over GA. ACO-DRL performed worse than ACO in this cluster.

Cluster 2

Table 11: Results of Cluster 3

Metric	ACO	GA	ACO-DRL	Best Model
CO2 Emissions (kg)	133.41	6996.07	227.27	ACO
Improvement over GA	98.09%	-	96.75%	ACO
Improvement over ACO	-	-	-70.35%	ACO

Best Performing Model: ACO, with a 98.09% improvement over GA. ACO-DRL did not outperform ACO in this cluster.

Cluster 2

Table 12: Results of Cluster 4

Metric	ACO	GA	ACO-DRL	Best Model
CO2 Emissions (kg)	156.58	4742.70	160.82	ACO
Improvement over GA	96.70%	-	96.61%	ACO
Improvement over ACO	-	-	-2.71%	ACO

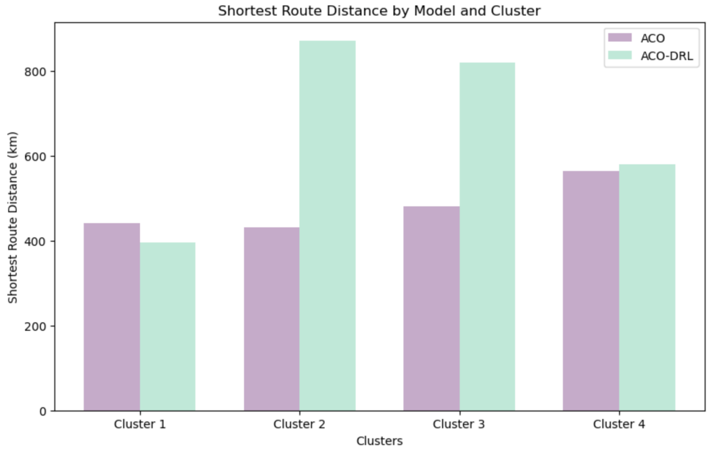

Figure 7: Shortest route distance by model and cluster

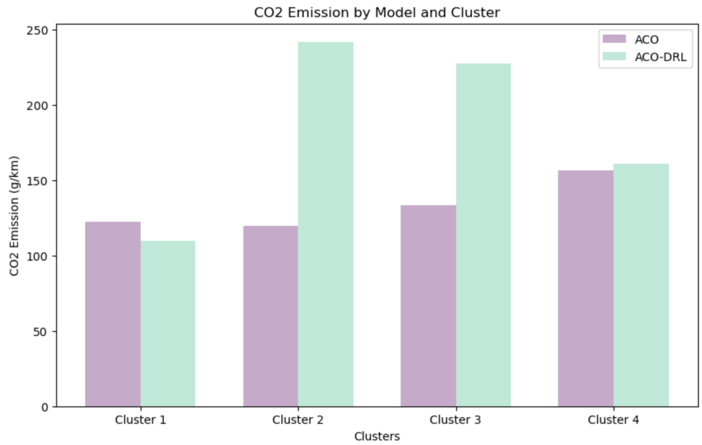

Figure 8: Co2 emissions by model and cluster

Best Performing Model: ACO-DRL with 97. Achieved 65% better than GA and 10. 49% improvement over ACO.

Overall Best Performing Model: ACO, with a 96. 70% improvement over GA. CO2 emission revealed that ACO-DRL had slightly raised the figure compared to ACO. Therefore, the best cluster is Cluster 0 for ACO-DRL model had the highest improvement over both GA and ACO. In Cluster 1, 2, and 3 where ACO dominated over GA and ACO-DRL, the ACO model was the best overall performer.

6.5 Discussion

The discussion section critically assesses the results of the experiments, the methodology and contextualize the findings within the framework of the research question as well as the literature.

ACO Model Performance

CO2 emission analysis: The analysis of the CO2 emission showed that the ACO model provided the lowest emission in all the four clusters with an overall emission of

532. mass of 20 kg and a total distance of 1919. 91 km. This is in line with the research objective which seeks to achieve the least distance and environmental influence. Nevertheless, as we saw, ACO's performance was rather strong, but it has to be noted that the model depends on the selected parameters to a significant extent. The fixed parameter of numbers of ant and pheromone evaporation rate might not have been the best for every cluster to some extent therefore might not have been adaptable. This points to a limitation of the experimental setting, and the results would have been even better if dynamic environments or real time parameter optimization was used on ACO.

Critical Evaluation:

• Strengths: ACO gave reductions in CO2 emissions that were also consistent and were slightly lower than GA and ACO-DRL.

• Limitations: Relevant information dependency on fixed parameters; better performance can be achieved with dynamic changes in the parameters.

GA Model Analysis

The GA model was far from the mark showing a total emission of CO2 as 22,077. A mean weight of 36 kg and a total distance of 79,644. 15 km. This is because GA model has been faced with early convergence as a major factor in their poor performance. The mutation rate and crossover rate of the model were predetermined which may not have been ideal for the nature of the problem.

Critical Evaluation:

• Strengths: Using the GA model as a reference, the performance of ACO and ACO-DRL was compared.

• Limitations: High CO2 emissions and long route distances; vulnerable to early convergence.

ACO-DRL Model Evaluation

The ACO-DRL hybrid model showed the promising results; especially in Cluster 0, the lowest CO2 emissions of 109 was realized. 200 grams less in weight at 84 kg and distances 396 in total. 25 km. But the performance was unimpressive in other clusters, which made a total CO2 emission of 739. 81 kg and a total distance of 2,668. 85 km. In some clusters, it is identified that the DRL model may have overfitting to the initial routes given by ACO and thus, the subsequent refinements are not as good as expected. Strengths: ACO-DRL revealed that the model has the capability to realise huge CO2 emission cuts and especially within Cluster 0.

The results of this research are in line with the existing literature regarding the applications of ACO in solving routing problems. The underachievement of the GA correlates with previous research, which outlines its drawbacks in large scale problems because of factors such as premature convergence. The mixed findings of the ACO-DRL model to some extent form part of the mixed literature on the application of hybrid optimization approaches. In the past, findings have revealed that there are advantages to using multiple algorithms, but this research affirms that this can only be obtained if the integration and tuning of the various algorithms are properly done.

7 Conclusion and Future Work

• ACO gives the best results, While evaluating the results of the ACO model, it is possible to observe that the emission of CO2 is considerably lower than with GA, equal to 97. 59% improvement

Table 13: Conclusion

Model	Total CO2 Emissions (kg)	Improvement Over GA (%)	Improvement Over ACO (%)	Best Performing Model
ACO	532.20	97.59%	-	ACO (3 clusters)
GA	22077.36	-	-	-
ACO-DRL	739.81	96.65%	-39.01%	ACO-DRL (1 cluster)

• GA: The GA model has the highest CO2 emissions hence making it the least efficient model for this problem.

• ACO-DRL: ACO-DRL improves the performance of the GA with 96.65% but does not overcome ACO in general, although in Cluster 0 it was the best model. In terms of the average reduction of CO2 emissions, ACO is the best model giving the most consistent decrease in the emissions in the majority of clusters. ACO-DRL has possibility in certain conditions.

A limitation of this study is that the authors only set fixed values of the parameters for each model, which might have restricted GA and ACO-DRL. However, the study lacked consideration of dynamic environmental factors, which are characteristic of the real-life context of logistics. The static aspect of the problem could have restricted the generalization of the outcomes to more dynamic problems in real-life situations.

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