Optimising Delivery Routes Under Real-World Constraints: A Comparative Study of Ant Colony, Particle Swarm and Genetic Algorithms

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***Abstract*—Effective logistics systems are essential for fast and economical package delivery, especially in urban areas. The intricate and ever-changing nature of urban logistics makes traditional methods insufficient. Hence, requirements for the application of sophisticated optimisation techniques have increased. To optimise package delivery routes, this study compares the performance of three popular evolutionary algorithms: ant colony optimisation (ACO), particle swarm Optimisation (PSO), and genetic algorithms (GA). Finding the best algorithm to minimise delivery time and cost while taking into account real-world limitations, such as delivery priority. This guarantees that deliveries with a higher priority are prioritised over others, which may substantially impact route optimisation. We examine each algorithm to create the best possible route plans for delivery trucks using actual data. Several factors are employed to assess each algorithm's performance, including robustness to changes in environmental variables and computational efficiency—the simulation models delivery demands using actual data. Results indicate that ACO performed better in Los Angeles and Chicago, completing the shortest routes with respective distances of 126,254.18 and 59,214.68, indicating a high degree of flexibility in intricate urban layouts. With the best distance of 48,403.1 in New York, on the other hand, GA achieve good results, demonstrating its usefulness in crowded urban settings. These results highlight how incorporating evolutionary algorithms into urban logistics can improve sustainability and efficiency.**

***Keywords*—Evolutionary algorithms; genetic algorithm; particle swarm optimisation; ant colony optimisation; urban logistics; route optimisation**

I. INTRODUCTION

Over the last few decades, global greenhouse gas emissions have increased considerably, which are widely considered as the primary contributors of climate cshange [1]. Meanwhile, there has been a growing consciousness of the environmental impacts of business activities, encouraging companies, researchers and governments to discover optimal solutions that support operations with sustainability principles within logistics. Logistics lead to a large dimension of greenhouse gases, making it essential to adopt greener and more sustainable logistics systems [2], [3], [4]. Such efforts not only benefit the planet but also cater to an increasingly eco-conscious human population. Sustainability has increasingly become a concern among academics and practitioners in the fields of logistics and supply chain management. Although research in this area has progressively increased, it still presents multiple directions worthy of exploration [3], [5], [6]. In particular, there is a crucial need for investigations that illuminate how businesses approach sustainability and how organisations and researchers can develop more sustainable supply chains. Enhancing the sustainability of supply chains is considered a fundamental strategic action towards achieving sustainable development goals. Logistics and supply chain performances account for at least one-third of energy consumption and one-third of GHG emissions [7]. To moderate these effects, it is essential to adopt a systemic approach to transformative change in our supply chains—from production to distribution—to enhance their sustainability. It is essential to consider the effects of supply chains and logistics on sustainability from social and economic perspectives. This includes issues with equity, labour conditions and employability. Logistics was first used in the military to describe the methods used by soldiers to acquire, store and transport supplies and equipment [1]. Managing the movement of resources throughout the supply chain is the focus of logistics, a term that is now frequently used in the corporate world, particularly in manufacturing [8]. This covers gathering, storing and moving resources to their intended locations. In the context of logistics, sustainable transport refers to the application of procedures and tools that lessen the impact of transportation and distribution operations on the environment. This idea goes beyond just transporting products from one place to another; it takes into account the environmental impact of these activities [9]. The goals of sustainable logistics are to maximise resource utilisation, minimise greenhouse gas emissions and lessen air and water pollution [5]. Furthermore, businesses can minimise the number of trucks required for deliveries by optimising delivery routes, which can save fuel expenses and maintenance costs and can enhance resource efficiency. In addition, it will enhance customer satisfaction. Companies can boost customer satisfaction and can encourage repeat business and customer loyalty by promptly and efficiently providing goods and services.

Many different optimisation techniques have been developed based on computational intelligence, such as evolutionary algorithms and solutions that opened up the domain of metaheuristics. This study compares the performance of three optimisation algorithms to determine which is better for scheduling problems in logistics: ant colony optimisation (ACO) [10], particle swarm optimisation (PSO) and genetic algorithms (GAs) [11]. The ACO algorithm is a probabilistic optimisation approach inspired by nature that finds the most effective paths in complex surroundings by simulating the foraging behaviour of ants. GAs are adaptive heuristic search algorithms that iteratively develop a population of solutions to address optimisation and search problems. They are based on the concepts of natural selection and genetics. PSO is another computational approach. It was motivated by the social behavior of fish schools and flocks of birds.

The paper aims to examine three models for logistic delivery optimisation using ACO, PSO and GA, addressing the particular difficulties presented by urban delivery environments. It aims to address a routing problem, where the objective is to determine the shortest path to deliver packages while accounting for the importance of each delivery. Priorities have an impact on the cost estimate. Thus, it is essential to manage more essential deliveries early in the route in addition to reducing the overall journey distance. In this paper, Los Angeles, New York and Chicago are used as study locations for package delivery optimisation research. By choosing these cities, we can address a wide range of variables and complexities that are reflective of worldwide urban logistics difficulties. These cities have a lot of business activity and e-commerce transactions, making them essential economic hubs. As a result, there are several delivery operations for both arriving and departing goods. Gaining knowledge from these cities will help in designing scalable, reliable and effective delivery methods that can be applied to different metropolitan environments globally. It will enhance the research's application value in real-world scenarios.

This study could add significantly to the topic of optimizing urban logistics in a number of ways. First, it offers an analysis of three popular algorithms (ACO, PSO, and GA) in relation to actual urban delivery problems, such as delivery priority. Second, the study assesses algorithm performance using a real data set, guaranteeing applicability and practical relevance. Third, the study provides useful insights for choosing the best method based on the particular needs of urban logistics by analyzing computational efficiency and route optimization accuracy.

The paper is structured as follows, the second section highlights previous research on the application of ACO, PSO, and GA in logistics and other relevant fields. The third section will introduce the methodology which we describe in the experimental design, including the setup of the optimization algorithms. This section also details the criteria for performance evaluation, focusing on delivery efficiency. The result section presents the findings from our simulations, comparing the effectiveness of ACO, PSO, and GA in optimizing delivery routes under urban constraints. The discussion section presents our findings for urban logistics systems. Finally, the conclusion section that addressed the key findings and discussed the broader implications for urban logistics optimization.

II. Literature Review

In this section, existing approaches and previous studies will be studied. Al-Tayar and Alisa [6] proposed several scenarios to obtain the optimal routing path in stochastic networks, including working according to static and dynamic network data. They used the evolutionary algorithm ACO to discover the optimal routing path between the source node and the target node witch's helpful to obtain optimisation that increases logistical effectiveness that leads to contributing to environmental sustainability by minimising fuel consumption, reducing emissions and conserving resources. However, there is a need to work on dynamic data in real time that can be modelled using other probability distributions.

Popović et al. [12] suggest to increase the efficiency of its logistics operations by improving the methodology for evaluating logistics processes using a new model. This model involves the creation of a novel grey full-consistency method which is used to calculate the weight values of the strengths, weaknesses, opportunities and threats factors of a logistics company However, because the application of the approach in the logistics field had not been considered previously, there are some limitations in developing the approach, such as the complex mathematical process for computing criteria weights even if it is applicable in evaluation processes in other various fields.

Zhai [13] proposed addressing the green low-carbon logistics path optimisation problem using the snowmelt heuristic optimisation algorithm. It starts by analysing the characteristics of the green low-carbon logistics path optimisation problem, then considers the optimisation cost and conditional constraints of the green low-carbon logistics path optimisation problem and uses the snowmelt heuristic algorithm model afterwards. The author compared the results with those of many different algorithms and discovered that the snowmelt heuristic algorithm achieves better performance overall but can easily fall into the local optimum problem.

Franco et al. [14] proposed a system that was designed by machine learning algorithms. To provide a solid and sustainable solution to make route adjustments such as re-routing and re-scheduling of the delivery for unpredicted cases, the possibility of a difference between the planned and the actual delivery routes, which is why the use of technology to respond efficiently to all possible events may happen. Even their conceptual framework still needs to be applied in different situations, adapted and extended, and at the same time, it helps in finding a common ground to feed data and obtain values, especially with a new tendency these days to synchronise digital technologies' penetration with all aspects of life.

Sadeghi and Haapala [15] expanded the research on previous work by incorporating the carbon cost into the mathematical cost to improve the mathematical model. The biomass-to-bio-oil supply chain (BTBSCS) used mobile and stationary bio-refineries and contributed to the literature on bio-oil problems by designing a genetic algorithm to obtain a near-optimal solution for establishing mobile and stationary bio-refineries to reduce logistical and carbon costs. Researchers must simultaneously improve the economic, environmental and social performance of bioenergy supply chains. Gao, Cao [16] focused on redesigning a new sustainable reverse logistics supply chain network with the existing forward logistics supply chain network by taking into account economic, environmental and social sustainability. Then, they proposed the MOSINP model to formulate the problem of sustainable reverse logistics supply chain network redesign. Their goal is to support logistics activities in the face of uncertain demand for new products and the return volume of products of multiple quality levels.

Weber et al. [17] proposed different optimisation problems to find suitable, qualified and optimal solutions for sustainability. The results of this study indicate that there are many improvement models that address the three dimensions of sustainability simultaneously and the social dimension of sustainability is the least studied aspect. An applied classification of mathematical modelling approaches used in sustainable societies is provided. Another research should shift the focus from models that deal primarily with economic and environmental aspects to more balanced models that include all three aspects of sustainability. This paper promotes the transparent and rapid communication of research that highlights the role of optimisation in interdisciplinary fields of mathematical programming and provides SI optimisation models with relevant sustainability indicators.

Zarbakhshnia et al. [18] suggested a probabilistic mixed-integer linear programming model for a sustainable forward and reverse logistics network problem that takes into account many products, stages, periods, and objectives. Their mode aimed to find a new environmental constraint and social matters in the objective functions as its innovation and contribution. This model is based on using a non-dominated sorting genetic algorithm. Their result achieved a better performance compared with a multi-objective PSO.

III. METHODOLOGY

ACO, PSO and GAs will be constrained in this paper. Metrics, including best route, distance, time computation consumption and environmental impact, will be the main topics of comparison. The goal was to find the best set of routes for vehicles that minimise the overall trip distance and cost given a set of delivery destinations, a depot and restrictions on vehicle capacity and delivery times. Every package in our delivery system has a priority feature that is dynamically determined by how likely it is to be delivered late. The 'late delivery risk' feature is a function that prioritises packages to reduce delays and improve customer satisfaction. The main objective is to guarantee on-time delivery by modifying operating priorities according to projected delivery dates and times.

A. *Ant Colony Optimisation (ACO)*

The ACO technique was inspired by the foraging behaviour of ant colonies, first introduced by Dorigo [10]. Ants are eusocial insects that rely on a community-based approach for survival, rather than existing as individual species. They communicate with each other through sound, touch and pheromones. Pheromones are chemical compounds secreted by ants that trigger social responses within the same species. These chemicals act similarly to hormones but are external to the body and affect the behaviour of other ants. Because most ants live on the ground, they also communicate by leaving pheromone trails on the soil surfaces, which can be detected and followed by other ants [19].

The ACO algorithm, a probabilistic optimisation strategy inspired by nature that finds the most efficient paths in complex surroundings by mimicking the foraging behaviour of ants, is used to tackle this task.

Because ants live in a community of nests, the fundamental idea of ACO is to track how ants leave their nests to get food by taking the shortest route possible. Initially, ants start randomly moving in the space around their nests to search for food. That randomised search technique opens up multiple possible routes from the nest to the food source. Ants now bring some of the food back with them, increasing pheromones along their route, depending on the kind and amount of food they discover.

Depending on these pheromone trials, the probability of selection of a specific path that has been performed by following the ants' path would be a guiding factor to the food source. Evidently, this probability is based on the rate of concentration and evaporation of pheromones. It can also be observed that when the evaporation rate of pheromones is also one of many different deciding factors, the length of each path can easily be accounted for.

- Pheromone Model: A pheromone matrix was initialised to influence the probability of including each city in a route.
- Construction of Solutions: Ants constructed solutions by probabilistically choosing the next city to visit based on a rule combining pheromone strength and a heuristic function (distance and priority).
- Pheromone Update: After all ants completed their routes, pheromones were updated based on the quality of the solutions, with more successful routes receiving higher pheromone levels.
- Daemon Actions: Optional global updates were performed to intensify or diversify the search.
- Iteration: The search continued until a stopping criterion, such as the maximum number of iterations for convergence, was met.

In his experiments, the pheromone updating process is modified as well as the solution representation to prioritise specific deliveries in (ACO). The updating of pheromone trails according to the nodes' priorities. This adjustment makes sure that during the optimisation process, high-priority deliveries are given preference and precedence over others.

Pseudocode for ACO

Input:

Distance matrix, Priority, Number of ants, Number of iterations, Evaporation rate ρ, Alpha α, Beta β

Initialize:
  Initialize pheromone levels on paths (tau)
  Initialize heuristic information (eta), such as 1/distance
  Initialize priority scores for nodes (priority)
For each iteration:
    for each ant:
      Place ant at a starting node
      while ant has not completed its tour:
        Select the next node based on transition

probabilities:
Move the ant to this next node
Optionally update pheromones on the path (local update)
Assess the quality of the ant's tour
Update pheromones based on the quality of the tour (global update)
Identify the best tour of the iteration based on lowest cost or highest priority fulfillment
Return the best overall tour found during all iterations

Therefore, the calculation takes into account the tour duration and a priority factor of this tour, which may depend on the nodes that the ant visited to update the pheromones. Routes that efficiently visit high-priority nodes can be prioritised by this factor.

B. Genetic Algorithm Optimisation (GA)

GAs are defined as adaptive heuristic search algorithms that belong to a larger part of evolutionary algorithms [11], [20]. They are predicated on concepts from genetics and natural selection. These are effective uses of the random searches made possible by past data to focus the search on the area of the solution space where performance is better. This is often used to produce solutions to search and optimization issues.

GAs have simulated the process of natural selection, which means that those species that can be able to change in the environment can survive, reproduce and go to the next generation [11]. In simply, that mimics the "survival of the fittest" by using individuals from succeeding generations to solve an issue. Every generation is made up of a population of individuals, and each individual is a potential solution as well as a point in search space. Every person has been represented as a bit string, integer, float, or string of characters. That string is analogous to the chromosome.

In this experiment, we modified the fitness evaluation to incorporate priorities. For instance, routes that visit high-priority locations earlier might receive higher fitness scores. The selection process will typically be implemented using methods such as roulette wheel selection, where the probability of an individual being selected is proportional to its fitness. This step ensures that higher-quality (higher fitness) individuals are more likely to be selected. The following section will describe the algorithm steps:

- Initialisation: The population was initialised with randomly generated possible routes. Each route or chromosome corresponds to a complete solution to the route.
- Fitness Function: The fitness of each chromosome was evaluated based on the total route distance, cost and adherence to delivery priority.
- Selection Process: A tournament selection process was used to select parent solutions for crossover based on their fitness scores.
- Crossover and Mutation: Ordered crossover (OX) and swap mutation were applied to generate new offspring, ensuring genetic diversity and exploration of the solution space.
- Termination: The algorithm terminated after a fixed number of generations or if there was no improvement in the best solution for a consecutive number of generations.

Pseudocode for GA

Input: Distance matrix, Priority, Population size N, Number of generations G, Crossover rate Pc, Mutation rate Pm, Fitness function F
Output: Best solution found
Initialize:
The population with N random solutions
Evaluate the fitness of each individual in the population using F
For each generation from 1 to G:
Select parents from the current population based on their fitness
Perform crossover on the parents to form new offspring, with probability Pc
Apply mutation to the offspring, with probability Pm
Evaluate the fitness of the new offspring using F
Select individuals for the next generation from the current population and the new offspring
If any offspring is better than the best solution found so far:
Update the best solution
Return the best solution

C. Particle Swarm Optimisation (PSO)

PSO has been inspired by a swarm of birds or a school of fish. At the same time, the algorithm is called a population-based stochastic algorithm, and it was developed by Russell et.al. in 1995. That is the overall concept of PSO and the basis of its biological phenomena [23]. In this paper, fitness should take priority into account in addition to the objective function (such as cost or distance), making sure that solutions that complete high-priority tasks are given a higher evaluation. The following section will explain the algorithm steps:

- Particle Representation: Each particle represents a potential solution to the route, encoded as a sequence of delivery points.
- Velocity and Position Update: Customised velocity and position update rules suitable for combinatorial problems were implemented, focusing on sequence operations, such as swaps, influenced by velocity vectors.
- Fitness Evaluation: Similar to GA, the fitness of each particle was assessed based on the route's total distance, cost and adherence to delivery priority.
- Global and Personal Best: Particles updated their velocities towards their personal best and the global best positions found during the search process.

- Convergence: The algorithm ran for a predetermined number of iterations or until performance plateaued.

Pseudocode for PSO

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Input: Distance matrix, Priority, Number of particles N, Number of iterations I, Inertia weight W, Cognitive component C1, Social component C2, Objective function ObjFunc
Output: Best known position gBest
Initialize swarm of N particles with random positions and velocities
    Evaluate the fitness of each particle using ObjFunc
    Set pBest of each particle to its initial position
    Set gBest to the position of the best performing particle in the initial swarm
    For each iteration from 1 to I:
        For each particle p in the swarm:
            Update velocity and position of particle p:
            Evaluate the fitness of the updated position of particle p
            If the fitness of the updated position is better than the fitness at pBest:
                Update pBest to the new position
            If the fitness of the updated position is better than the fitness at gBest:
                Update gBest to the new position
  Return gBest
```

IV. Data Preparation

To verify the proposed sustainable logistics optimisation, an experiment has been designed and the experimental data are an extension of an open-source reference to address the logistics optimisation problem. In our experiment, the dataset used contains 25837 rows and 53 columns, with three cities being selected from that dataset (Chicago, New York and Los Angeles). Each city has several predefined delivery locations (latitude, longitude). Each location will have associated package delivery requirements, including package priority (late delivery). The priority information feature, that is, each algorithm's decision-making, is influenced by the corresponding priorities assigned to each node. The probability of reaching that node sooner increases with higher priorities.

The dataset was prepared before starting use in this study using many different techniques to ensure that any blanks are removed. In addition, there are no duplications or symbols in the dataset. Table I shows the number of addresses in each city.

TABLE I. Data Set

City	***Number of address***
Chicago	3885
Los Angeles	3417
New York	1816

This experiment adapts PSO to a complex permutation issue by reinterpreting the particle movement in the solution space, effectively using swaps influenced by pseudo-velocity. An element of complexity common to scheduling and logistics operations in the real world is added by the adaption, which involves managing priorities in route planning. This method exemplifies the adaptability of PSO and its potential for combinatorial optimisation beyond conventional uses.

Performance was evaluated based on the quality of the solution (total travel distance and cost), computational time and robustness against variations in problem parameters. A combination of the distance and strategic significance of the nodes visited may be used to determine which tour is optimal for each iteration, with an emphasis on routes that better meet higher-priority requirements.

V. Results and Evaluation

In our experimental setup, we implemented three well-known optimisation algorithms, namely, ACO, PSO and GA, to address a complex delivery routing problem and priority considerations. Each algorithm was configured with specific parameters tailored to balance evaluation and manipulation as shown in Table II, with ACO using 10 ants, PSO comprising 30 particles and GA operating with a population of 100 individuals. Our scenarios, which were generated from real-world data, involved more than 1000 delivery points with diverse priority levels. Each algorithm was executed 10 times per scenario to ensure robustness, with results focusing on efficiency, compliance with time computational consumption priority constraints and computational performance.

TABLE II. Parameters of Algorithms

Parameter	***GA***	***PSO***	***ACO***
Population Size	population = 100	num_particles = 30	number of ant =10
Operators	Ordered Crossover (OX), simple swap mutation Implements tournament selection	Velocity Update	Pheromone Update
Crossover Rate	0.7	-	-
Mutation Rate	0.05	-	-
Stopping Criteria	number of generation 100	number of iteration 100	number of iteration 100
Coefficients	-	alpha=1.0, beta=2.0, evaporation=0.5	Alpha (pheromone importance) =1 Beta (heuristic importance) =1

In Fig. 1 to Fig. 9, the figures visualize the optimization process of each evolutionary algorithm, where the Y-axis represents the best fitness value and the X-axis refers to the number of generations. This axis shows the number of generations through which the algorithm has been processed. As can be seen from Fig. 1 to Fig. 9, the performance of each algorithm improves with each iteration, as indicated by the decreasing score of the best distance. The performance of the GA algorithm improves consistently across all three experiments. In contrast, PSO shows that an increase in the number of iterations does not necessarily enhance its performance.

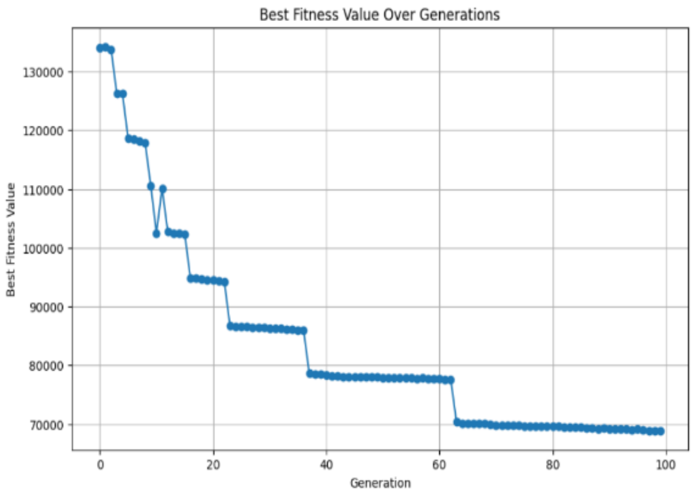

Fig. 1. Performance of GA for New York.

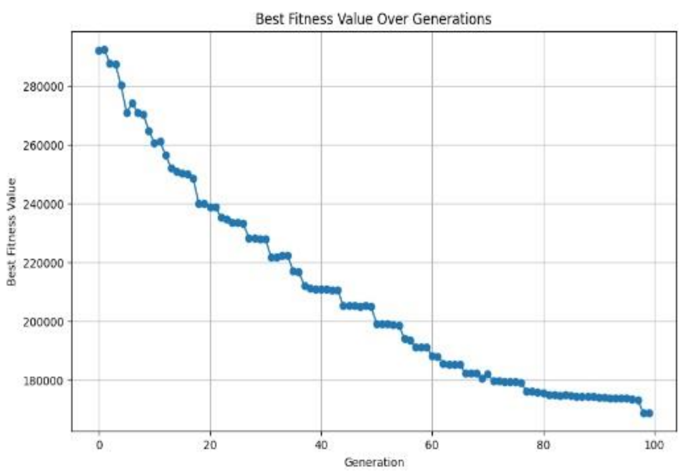

Fig. 2. Performance of GA for Chicago.

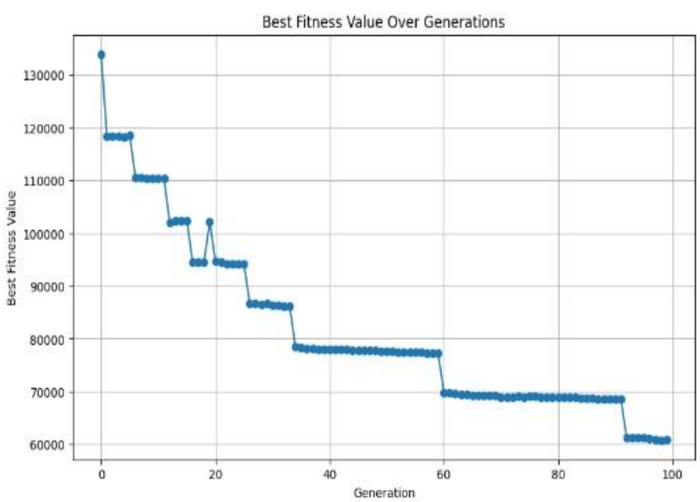

Fig. 3. Performance of GA for LA.

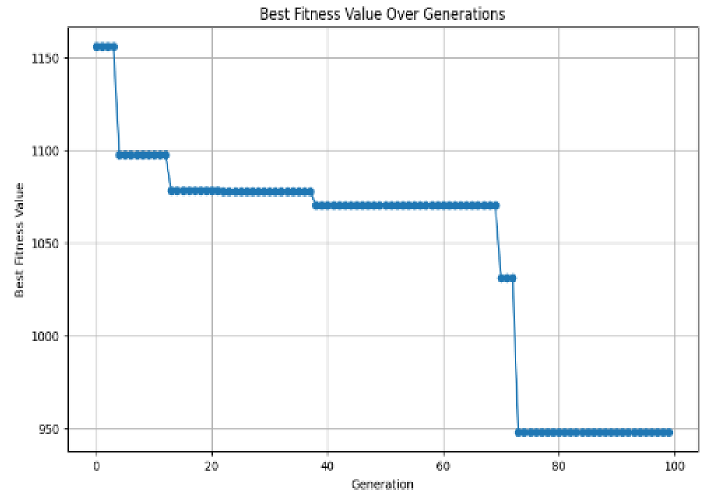

Fig. 4. ACO performance for LA.

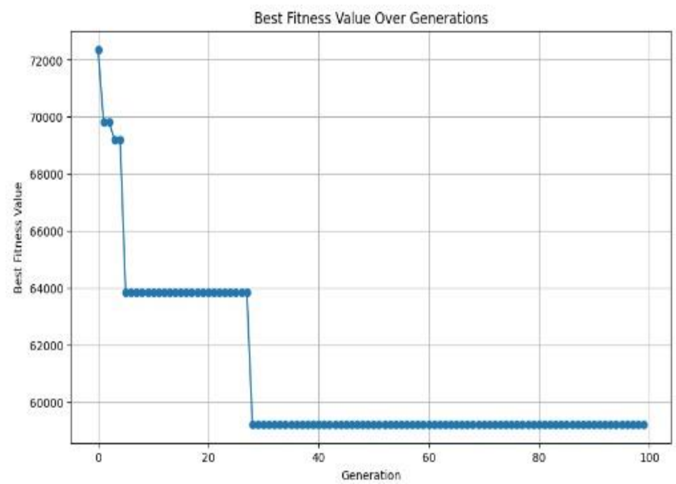

Fig. 5. ACO performance for Chicago.

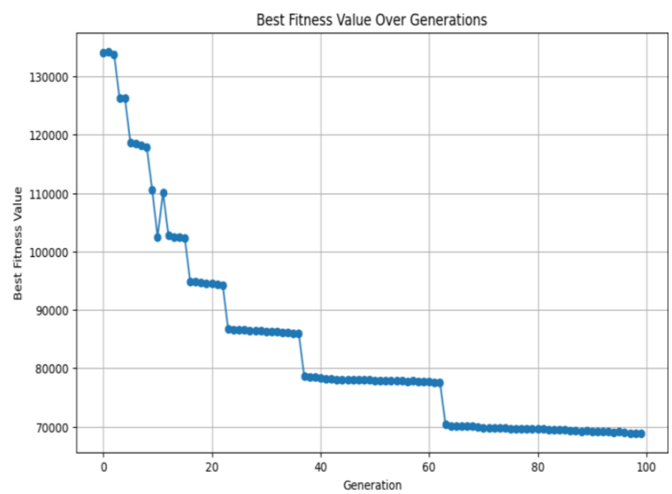

Fig. 6. ACO performance for New York.

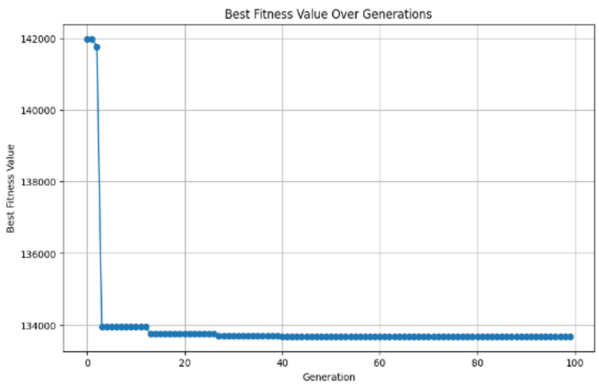

Fig. 7. PSO performance for LA.

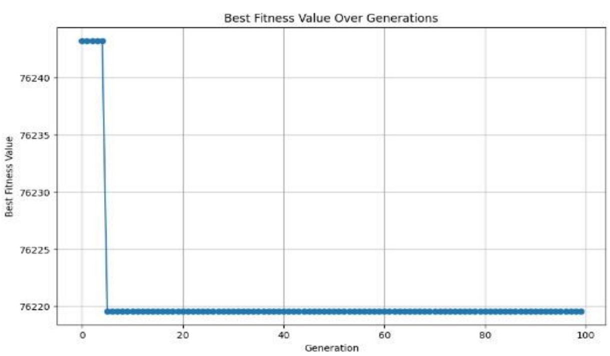

Fig. 8. PSO performance for New York.

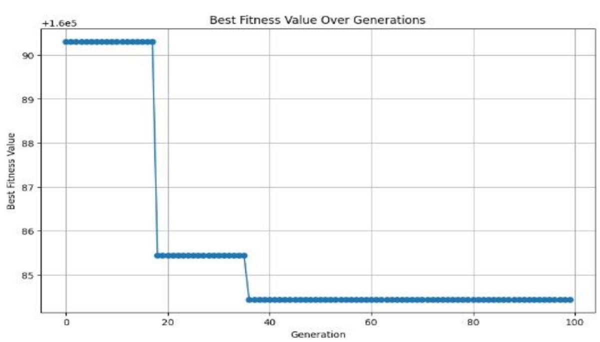

Fig. 9. PSO optimisation performance for Chicago.

Table III shows the result of each algorithm. The best performance was achieved by ACO for Chicago and LA, where the lowest performance was achieved in New York. However, when focused on time consumption, PSO is the fastest algorithm, and this is related to the lowest computational complexity in the algorithm procedure.

TABLE III. RESULT OF THE THREE OPTIMIZATION ALGORITHMS

Data set	**Evaluation matrix**					
	The best distance			***Time***		
	ACO	***GA***	***PSO***	***ACO***	***GA***	***PSO***
Chicago	59214.681	169017.6	160084.44	1156.282	285.6	27.92
LA	948.1877	60893.05	70260.64	560.4	130.49	20.59
New York	126254.18	48403.1	76219.58	8173.28	180	12.11

VI. DISCUSSION

Different performance characteristics for each algorithm under the urban package delivery scenario were revealed by our comparison investigation of GA, PSO and ACO. ACO had the best overall efficiency, the quickest delivery times and the lowest operating expenses. This was followed by GA, which demonstrated strong performance but was less efficient in terms of time and cost, and ACO, has achieved the best score based on time consumption.

The efficacy of ACO in our investigation is consistent with previous research that emphasizes its advantages in continuous optimisation issues, which we have converted to a discrete context by carefully adjusting parameters.

Given that ACO performed better in our simulation, its implementation may greatly improve operational effectiveness in urban logistics. Urban delivery services might undergo a revolution as a result of the shorter delivery times and cheaper operating costs, which would benefit consumers by lowering prices and increasing profitability for logistics companies. ACO's capacity to address constraints, such as the delivery priority problem, demonstrates its usefulness in scenarios where route dependability is crucial, reinforcing the suggestions made by [21] for logistics applications. In multi-objective logistical scenarios, GA demonstrated its versatility as observed by [22], as evidenced by its competitive performance to achieve a good result even with constraints.

This modified ACO algorithm works especially well in delivery and logistics settings where some deliveries are more essential than others possibly because of commodities that must be delivered on time. It enables the algorithm to automatically modify its pathfinding to give these crucial nodes a higher priority, mirroring operational priorities found in automated decision-making systems in the real world. Furthermore, ACO may be especially helpful in situations where late deliveries result in significant fines, such as in the case of medical or just-in-time industrial supplies, because of its high reliability in meeting delivery timetables.

Our results have several noteworthy implications, one of which is the possibility of minimising environmental effects through optimal routing. The effectiveness of ACO could contribute to decreased emissions and fuel consumption, which helps sustainability objectives in logistics and urban planning. This is essential as cities worldwide work to address climate change and lower their carbon footprints.

Although results show promise, they are restricted to simulated settings and might not accurately represent the intricacies of human dynamics and real-world traffic patterns. To evaluate and improve the models, future research should try to apply these algorithms in real-time logistics operations, possibly through pilot programmes.

VII. CONCLUSION

This research not only confirms that ACO, PSO and GA are appropriate for optimising urban logistics but also creates chances for integrating these algorithms into practical uses. Through extensive simulations and analysis, we coucnlued that these algorithms could significantly enhance operational efficiency by optimizing delivery routes. Our data indicated that ACO, especially, excelled in handling complex urban environments by adapting to dynamic constraints. The integration of these algorithms into real-world data set shows promising potential to improve the operational success of logistics firms. By implementing these optimized strategies, companies can more reliably meet delivery schedules. The practical deployment of these methods led to a measurable improvement in punctuality and efficiency, as evidenced by the decrease in average delivery times and which will increase customer satisfaction rates.

Finally, this paper focused on the problem of package delivery route optimisation in heavily populated urban states with obtained results. We recommend modifying the ACO algorithm as a solution. Throughout the project, an effective model that addressed the problems with urban delivery was created, and using outside literature, we assessed the effectiveness of our approach using a variety of indicators. Although benchmark tests were ideal solutions, our findings were affected by algorithmic complexity and real-world application considerations. Overall, with space for improvement and parameter adjustment, our ACO-based approach provided insights into effective route planning for food delivery services in urban settings.

Because traffic congestion constantly develops in urban areas because of an increase in traffic vehicles, this project is advantageous for traffic routing in urban areas with more complex types of roads. This package delivery route optimisation project can be performed on a bigger scale, for example, by creating a routing system for an entire nation's traffic network. The data and performance measures that were covered in this project can help with upcoming studies and initiatives that might use them as a point of reference.

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