Swarm Intelligent Approach for Vehicle Routing Problem

Abstract

The Vehicle Routing Problem (VRP) is a complex logistical task involving optimal route planning for a fleet of vehicles to deliver goods to customers while minimizing costs and following constraints. Due to its complexity, the VRP belongs to the NP-hard problems category, which means finding the best solution becomes tougher as the problem grows, leading to significant computational and time requirements. As a result, many researchers are working on this problem using different approaches to create inventive solutions. These vary from precise algorithms, great for small cases but struggling with larger ones, to heuristic and metaheuristic methods that offer nearly optimal solutions promptly. Among different approaches, Swarm Intelligence is one of the promising approaches to solving complex problems. This project focuses on developing a hybrid swarm intelligence algorithm to solve vehicle routing problems. This hybrid strategy aims to leverage swarm intelligence's potential to tackle the challenges posed by VRP complexity, delivering efficient solutions for real world logistics scenarios.

Acknowledgment

We would like to express our sincere gratitude to our project mentor, Dr. G Hanumat Sastry, for his invaluable guidance and support throughout the Project on "Swarm Intelligent Approach for Vehicle Routing Problem". His expertise in the field of AI and optimization algorithms proved instrumental in shaping our project. The insightful discussions, constructive feedback, and unwavering encouragement were crucial in helping us navigate the complexities of the research and development process.

We are incredibly grateful for his mentorship, which has enriched our understanding of Vehicle Routing Problems and Swarm Intelligence algorithms. We have learned not only the technical aspects of the project, but also valuable skills such as critical thinking, problem-solving, and collaboration.

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1 Introduction

Vehicle Routing Problem (VRP) stands as a critical puzzle in logistics and transportation, demanding solutions that minimize costs, travel duration, distance, and vehicle utilization [1,2]. Over recent years, scientists have shown significant interest in VRP due to its potential for cost reduction and sustainability. [3,4]

Harnessing Swarm Intelligence Swarm Intelligence (SI) draws inspiration from social animals like ants, bees, and birds, presenting a theoretical basis for solving complex problems [4,5]. Notably, algorithms such as Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) have effectively tackled optimization challenges [6,7].

PSO and GWO in VRP PSO, conceived in 1995 by Dr. James Kennedy and Dr. Russell Eberhart, mirrors bird-swarming behavior, excelling in exploring solution spaces and adapting to changing conditions [11]. Its versatile nature finds applications across diverse fields, including VRP [12].

GWO, a 2014 innovation by Seyedali Mirjalili, Shima Seyedali, and Andrew Lewis, replicates the hierarchical structure of wolf packs to swiftly optimize vehicle routes, blending hunting strategies into problem-solving methodologies [9,13].

A Synergistic Solution By integrating the strengths of PSO and GWO, researchers aim to forge a robust strategy for complex routing issues that surpass individual algorithmic capabilities [8][10].

Evolution of VRP Solutions The evolution of VRP solutions spans decades, encompassing heuristic, exact, and hybrid algorithms, alongside real-world applications [14]. Advancements in computing technologies have empowered the development of sophisticated algorithms, catering to dynamic client needs and traffic changes.

Embracing Sustainability and Innovation Modern trends in VRP include eco-friendly routing systems, multi-objective variations, and strategies considering sustainability, reflecting a shift towards addressing complex trade-offs [15].

Future Frontiers in VRP To further invigorate VRP solutions, suggestions include exploring data-driven approaches, sustainability focus, hybrid algorithms, and quantum computing, foreseeing advancements fueled by technological breakthroughs and evolving logistics landscapes [16]. The VRP's evolution mirrors the perpetual challenges and opportunities in optimization, with future strides hinging on technological breakthroughs and adapting to the logistics and transportation ecosystem.

2 Problem Statement

The vehicle routing problem shows how things are delivered from one/more depots that have a given set of vehicles that can move on a given road network to a set of customers. Mathematically, it can be defined using graph theory, where a directed graph represents the locations (nodes) and the paths (edges) between them.

Let G = (V, E)

Where, V = 0,1,2,3,. . . .,n , in which 0 is the depot(starting and ending point of each vehicle), and 1,2,3,. . . ., n are the customer locations. Figure 1. represents the vehicle routing problem.

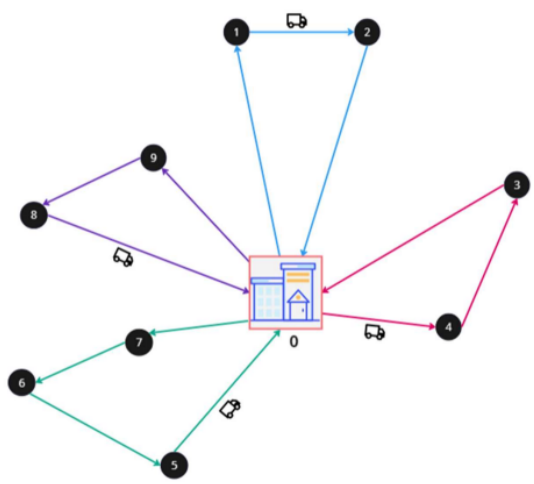


Figure 1: A high-level graphical representation of Vehicle Routing Problem

Let E be the set of edges (i, j) : i, j V , i j , each associated with a weight C i,j is the cost of travelling from vertex i to vertex j.

Constraints:

Capacity Constraint: Each vehicle has a limited carrying capacity, and the total demand of the customers assigned to a vehicle must not exceed this capacity.

Time Constraint: Each customer has a specified time window during which it can be serviced. Vehicles must follow the time window to ensure deliver goods.

Starting and Ending Point Constraint: The routes for each vehicle should start and terminate at a common depot or initial point.

This provides a clear and concise roadmap for the research problem, and helps to ensure that this project is well-designed and addresses a significant and relevant issues.

3 Literature Review

References	Findings	Applications
The Vehicle Routing Problem: State of the Art Classification and Review [2]	States how ‘Vehicle Routing Problems’ have evolved over time and also about the advancements of solutions and applications over the decades. It includes the general notations that are used for popular VRP variants and the classification of the academic literature on the VRP	The results show that there is a wide variety of VRP problems, therefore real-life characteristics are essential to include so that the model becomes more realistic and the proposed solutions are more applicable.
Particle Swarm Optimization [11]	Introduces the relationship between Particle Swarm Optimization and artificial life. The main purpose of this paper is to optimize the continuous nonlinear functions. It reviews its stages from being a social simulation to optimization and describes the ease of implementing it which requires simple code and a few operators	The main objective of this paper is to optimize the nonlinear continuous functions of real-world problems. This paper shows how PSO can be used to enhance wind speed forecast keeping in mind factors such as wind speed, wind direction, relative humidity, precipitation and air pressure.
Grey wolf optimizer [13]	The paper describes how GWO is better than other swarm intelligent algorithms being simple, scalable, flexible and easy to use. It consists of a detailed introduction to GWO along with procedural details of its main operations. The categorization of recent versions of GWO is studied further in a detailed manner.	This paper discussed the real-world applications of GWO, including the machine learning applications, engineering applications, medical and bioinformatics applications, and wireless sensor network applications and image processing applications.

References	Findings	Applications
Grey Wolf Optimizer paper by Seyedali Mirjalili, Seyed Mohammad Mirjalili, Andrew Lewis [13]	Proposed meta-heuristic method inspired by grey wolves which mimics their social hierarchy and hunting behavior and demonstrated GWO provide better results than other well-known meta-heuristic approaches.	This article demonstrates how GWO can be used to enhance constrained problems in classical engineering. A real-world application is also discussed in this article, which is to optimize the structure of Photonic Crystal Waveguide(PCW) which is an important component of optical CPUs.
Solving the CVRP Problem using a hybrid PSO approach [10]	The paper aims to develop a hybrid algorithm model combining two different algorithms (Particle Swarm Optimization and Simulated Annealing) to solve Vehicle Routing Problems in a better way.	The algorithm proposed in the paper can solve CVRPs in a reasonable time for real world scenarios.

4 Project Objective

- To develop and implement a hybrid optimization algorithm that combines, Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) techniques for addressing the Vehicle Routing Problem.
- To minimize the number of vehicles needed to serve all the customers.
- To find the optimal solution of the VRP nearer to the global optima.

5 Methodology

Vehicle routing problem can be described as follows: a fleet of vehicles has to visit a number of customers with some demands located in various cities. It involves finding the most efficient way to deliver goods or services. The primary objective is to minimise transportation costs and, in some cases, minimise the number of vehicles used while satisfying various constraints.

The proposed work aims to achieve improved results, by hybridising the Swarm Intelligent Approaches, Particle Swarm Optimisation (PSO) with Grey Wolf Optimizer (GWO). The proposed algorithm has mainly two phases. (Figure 2.) 1. The exploration phase 2. The exploitation phase

Particle Swarm Optimisation (PSO) will be employed in the exploration phase. The function f(X) produces a real value from a vector parameter X (such as coordinate (x, y) in a plane). The PSO algorithm will return the

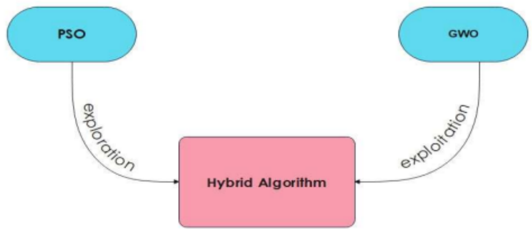


Figure 2: Representation of the hybrid algorithm

parameter X that produces the minimum of f(X). The position of a particle i at iteration t is denoted.

$$X^i(t+1) = X^i(t) + V_x^i(t+1)$$

$$x^i(t+1) = x^i(t) + v_x^i(t+1)$$
$$y^i(t+1) = y^i(t) + v_y^i(t+1)$$
$$V^i(t+1) = wV^i(t) + c_1r_1(P^i - X^i(t)) + c_2r_2(G - X^i(t))$$

The exploitation stage (GWO phase) will be used for fine-tuning the hybridized algorithm to get an optimal solution.

$$D = |C.X_P(t) - X(t)|$$

$$X(t+1) = X_P(t) - A.D$$
$$A = 2a.r_1 - a$$
$$C = 2.r_2$$
$$D_\alpha = |C_1.X_\alpha - X|, D_\beta = |C_2.X_\beta - X|, D_\gamma = |C_3.X_\gamma - X$$

$$X_1 = X_\alpha - A_1.(D_\alpha), X_2 = X_\beta - A_2.(D_\beta), X_3 = X_\gamma - A_3.(D_\gamma)$$

$$X(t+1) = \frac{x_1 + x_2 + x_3}{3}$$

By combining the exploration strength of Particle Swarm Optimization (PSO) with the exploitation capabilities of Grey Wolf Optimizer (GWO), we aim to create a synergy that leverages the best of both variants. The initial step involves updating the positions of the particles in the search space using a set of unique mathematical equations given below. Unlike traditional equations, we introduce an inertia constant to control how the grey wolf explores and exploits the search space. This adjustment leads to a modified set of equations

$$D_\alpha = |C_1.X_\alpha - X|$$

$$D_\beta = |C_2.X_\beta - X|$$

$$D_\gamma = |C_3.X_\gamma - X$$

To seamlessly integrate the PSO and GWO variants, these are the following equations for velocity and position updates:

$$V^i(t+1) = w(V^i(t) + c_1 r_1(x1 - X^i(t)) + c_2 r_2(x2 - X^i(t)) + c_3 r_2(x3 - X^i(t)))$$

$$X^i(t+1) = X^i(t) + V_x^i(t+1)$$

Pseudocode:

Initialization:
Evaluate the fitness of particles
while (i ¡max no. of iterations)
for each search agent
Update the velocity and position
end for
Update x, a, w and c
Evaluate the fitness of all search agents
Update position first three agents
t = t + 1
end while
return // first best search agent position

Therefore, our approach is designed to find optimal or near-optimal solutions efficiently, thus significantly enhancing the quality of solutions compared to single-algorithm approaches.

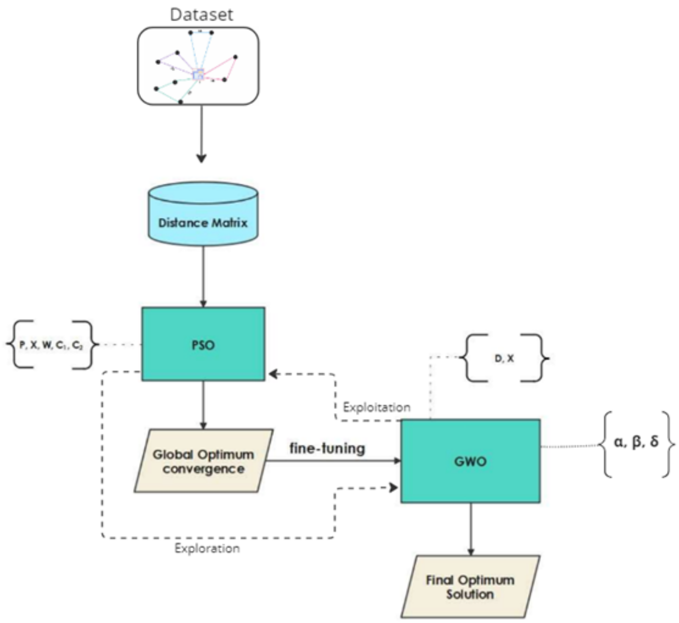


Figure 3: Flowchart representing integrated PSO-GWO Approach

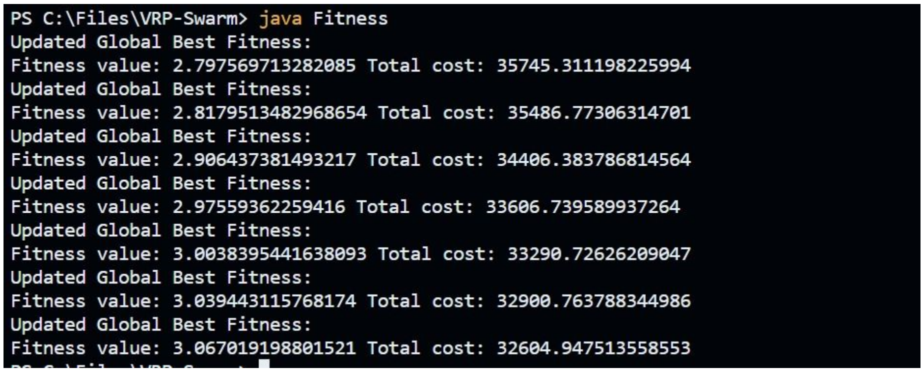
6 Results

In the experimental phase, real-world logistics scenarios were emulated using a representative dataset. After an extensive run of 1000 iterations, the results showcased a significant reduction in the total cost. Notably, this reduction was achieved while ensuring compliance with the capacity constraint for every vehicle, demonstrating the algorithm's efficiency in optimizing logistics solutions.

Furthermore, the experiment's outcomes revealed the algorithm's adaptability to varying conditions, emphasizing its robustness. The capability to consistently lower the total cost over multiple iterations signifies the algorithm's stability and reliability.

Moreover, the algorithm's ability to consistently lower the total cost over 1000 iterations implies its reliability in providing cost-effective solutions. This outcome bodes well for real-world logistics applications, offering a promising tool for companies looking to enhance their operational efficiency.

The graphical representation in Figure 4 visually captures the consistent improvement in total cost over the 1000 iterations. This graphical evidence reinforces the algorithm's effectiveness and provides a clear illustration of its performance trajectory under continuous iteration.



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PS C:\Files\VRP-Swarm> java Fitness
Updated Global Best Fitness:
Fitness value: 2.797569713282085 Total cost: 35745.311198225994
Updated Global Best Fitness:
Fitness value: 2.8179513482968654 Total cost: 35486.77306314701
Updated Global Best Fitness:
Fitness value: 2.906437381493217 Total cost: 34406.383786814564
Updated Global Best Fitness:
Fitness value: 2.97559362259416 Total cost: 33606.739589937264
Updated Global Best Fitness:
Fitness value: 3.0038395441638093 Total cost: 33290.72626209047
Updated Global Best Fitness:
Fitness value: 3.039443115768174 Total cost: 32900.763788344986
Updated Global Best Fitness:
Fitness value: 3.067019198801521 Total cost: 32604.947513558553
```

Figure 4: Optimized Routing Plan

7 Conclusion

Through the innovative integration of Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO), this project aims to capitalize on the complementary strengths of these two algorithms. PSO excels in global exploration, while GWO is adept at local exploitation. This hybrid approach balances exploration and exploitation, increasing the likelihood of converging toward superior solutions. The result is a more robust and effective optimization strategy for the VRP, bringing us closer to the global optimum. This improves route planning accuracy and contributes to more streamlined and effective logistics management.

8 Future Work

Integration of Advanced Artificial Intelligence Techniques: By leveraging the power of neural networks and advanced learning algorithms, we can enhance the model's adaptability and decision-making capabilities. This can lead to more intelligent and context-aware routing solutions, especially in dynamic and evolving logistical environments.

Real-World Application and Deployment: The extension of the current project into real-world applications is envisaged through collaboration with logistics companies and transportation agencies. The hybrid PSO-GWO solution can be implemented and deployed in operational settings to assess its performance under diverse and dynamic conditions. This practical application is anticipated to provide valuable insights into the scalability, robustness, and real-world efficacy of the proposed optimization approach. The research emphasizes the transition from a theoretical framework to practical, hands-on applications, contributing to the advancement of logistics and transportation optimization strategies.

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10 Program Listings

Github link : https://github.com/ankitakasibatla10/HybridSwarm$_V RP$